Land surface hydrology research at the University of Washington

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UNIVERSITY OF WASHINGTON

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UW LAND SURFACE HYDROLOGY RESEARCH GROUP 2012


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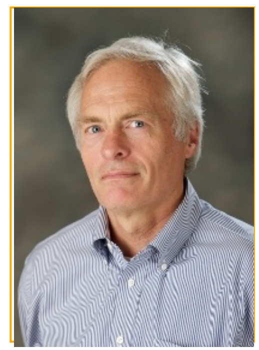
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Outline of this talk

1) Introduction
2) Example 1: Estimating methane fluxes from Northern Eurasian wetlands
3) Example 2: Seasonal hydrologic prediction
4) Example 3: Hydrologic applications of satellite altimetry
5) Conclusions

1) Introduction

1) What are the “big picture” problems in hydrology?
    a) Understanding hydrologic change
    b) Interaction of the water cycle with ecosystems
    c) Water quality and contaminant hydrology
    d) Hydrologic predictability and water management implications
2) What role does remote sensing play?

Example 1: Estimating methane fluxes from Northern Eurasian wetlands

Constraining Lake and Wetland Methane Emissions in West Siberia

T.J. Bohn[1], R. Schroeder[2,3], E. Podest[2], N. Pinto[2], K.C. McDonald[2,3], M. Glagolev[4], S. Maksyutov[5], and D.P. Lettenmaier[1]

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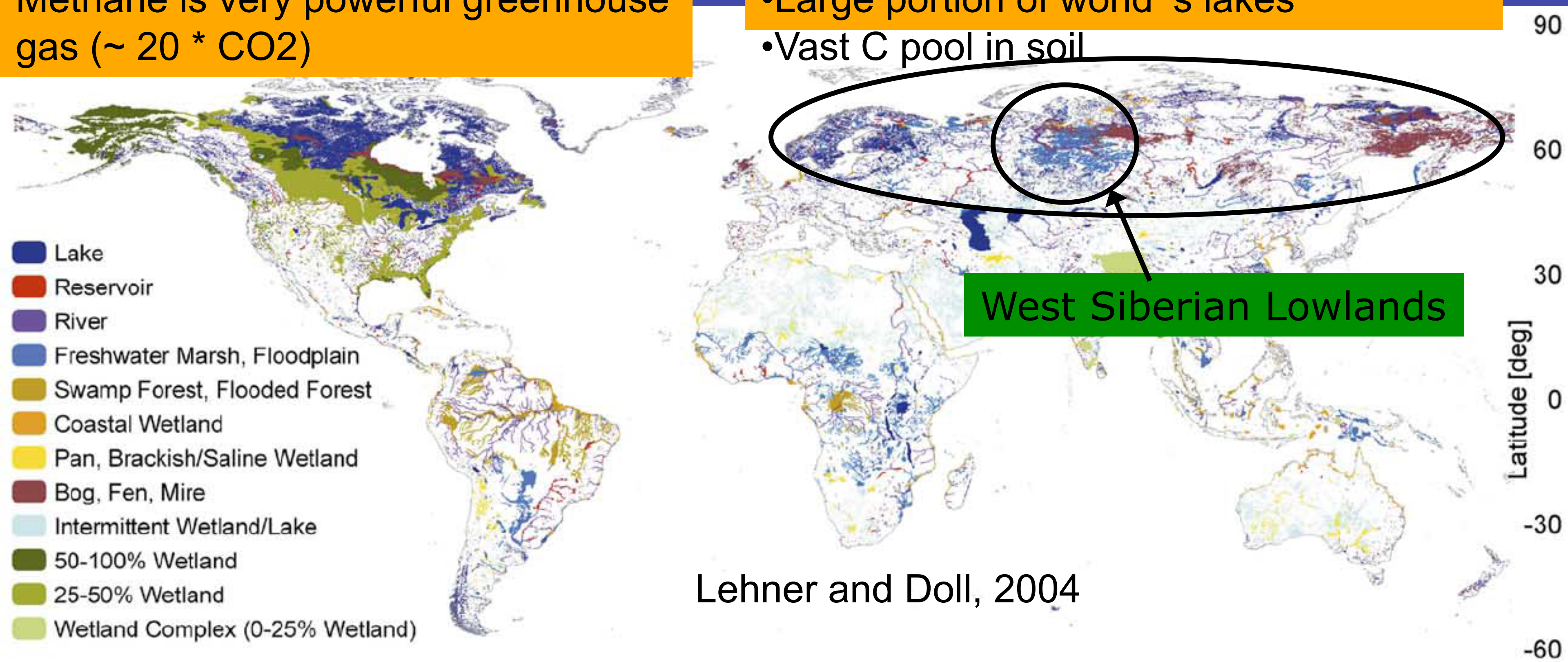
JPL-NASA, Pasadena, CA, USA, 2012-Feb-13

Why West Siberia?

Lakes and wetlands are the world's largest natural source of methane

Methane is very powerful greenhouse gas (~ 20 * CO_2)

Northern Eurasia contains:
- 30% of world's wetlands (Gorham, 1991)
- Large portion of world's lakes
- Vast C pool in soil



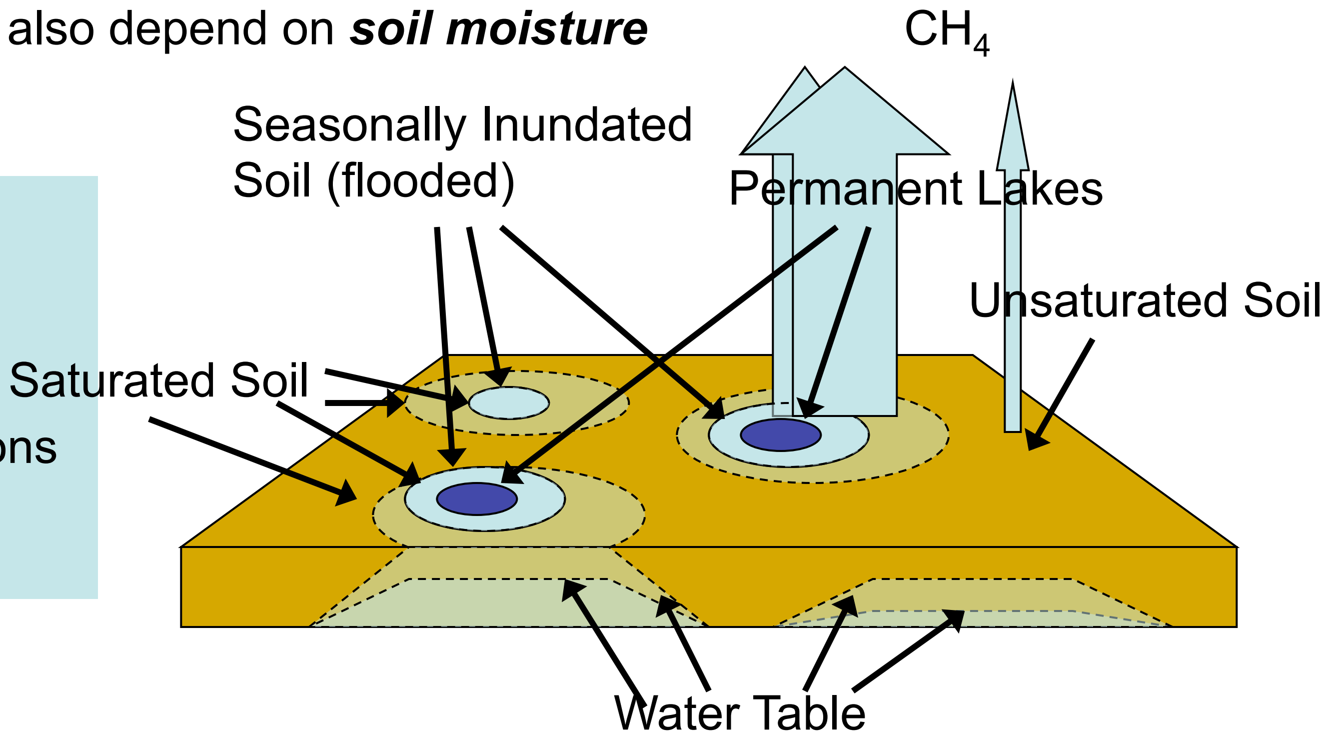
Lehner and Doll, 2004

High latitudes experiencing pronounced climate change: potential climate feedback

Lakes, Wetlands, and Methane

- Lake/wetland CH4 emissions depend on T, C, nutrients, oxidation state, etc
- Wetland CH4 fluxes also depend on ***soil moisture***

Neglecting any of these components can lead to large biases (+/- 30%) in projections of end-of-century methane emissions (Bohn and Lettenmaier 2010)



- ***Areal extent of wet zones can vary substantially in time***
- ***Areal extents are poorly-constrained***
- ***CH4 emissions rates are poorly-constrained***

Emissions components & Uncertainties

Lakes

- Areas uncertain
  - GLWD disagrees with passive microwave remote sensing products; GLWD is known to substantially underestimate lake extent in Siberia (Walter et al 2007)
- Emissions *very* uncertain – 10 to 1000 mg CH4/m2/day

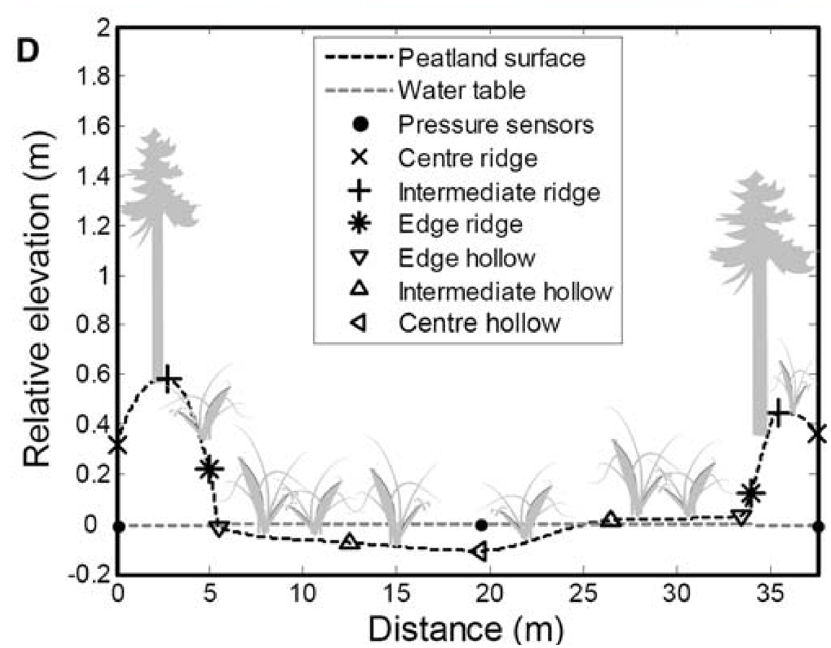
Saturated Wetlands

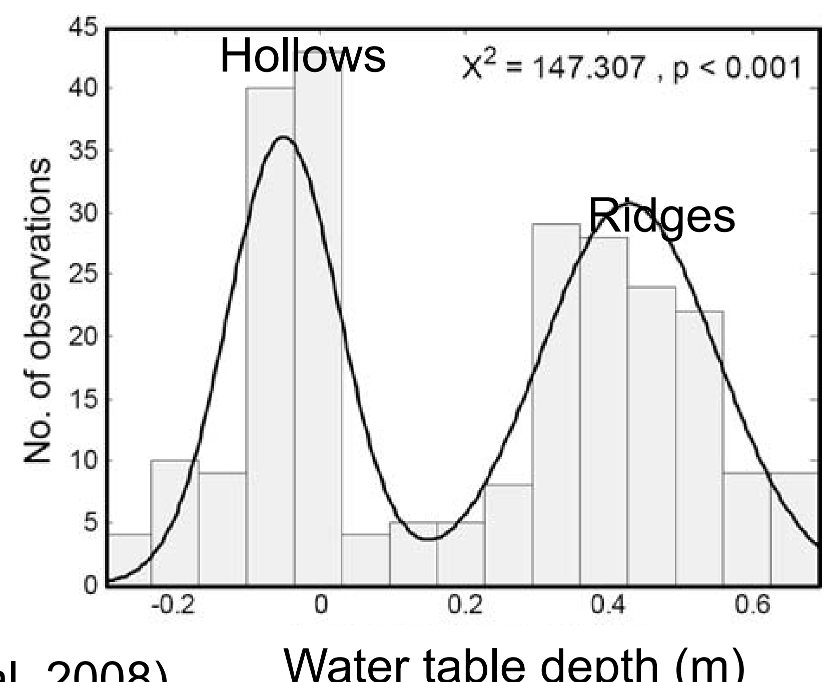
- Area of saturated zone uncertain
- Two sub-components
  - Inundated (standing water)
    - Can be observed by passive and active microwave remote sensing
  - Exposed (wet but no standing water; covered by veg)
    - Passive microwave not so good at seeing this
- No oxidation in soil == Maximum CH4 emissions

Emissions components & Uncertainties (cont.)

Unsaturated Wetlands

- Uncertain distribution of water table depths
- Depends on microtopography
- Some oxidation in soil == Lower CH4 emissions





(Eppinga et al, 2008)

How to Estimate?

Saturated Extent
- Calibrate model to passive microwave observations of total surface water
- Use model prediction of saturated soil extent

Water Table Distribution
- Use VIC parameterization of water table depth enhanced with representation of microtopography

Lake areas
- Try two scenarios:
  - GLWD (Lehner and Doll, 2004)
  - Minimum annual surface extent given by passive microwave

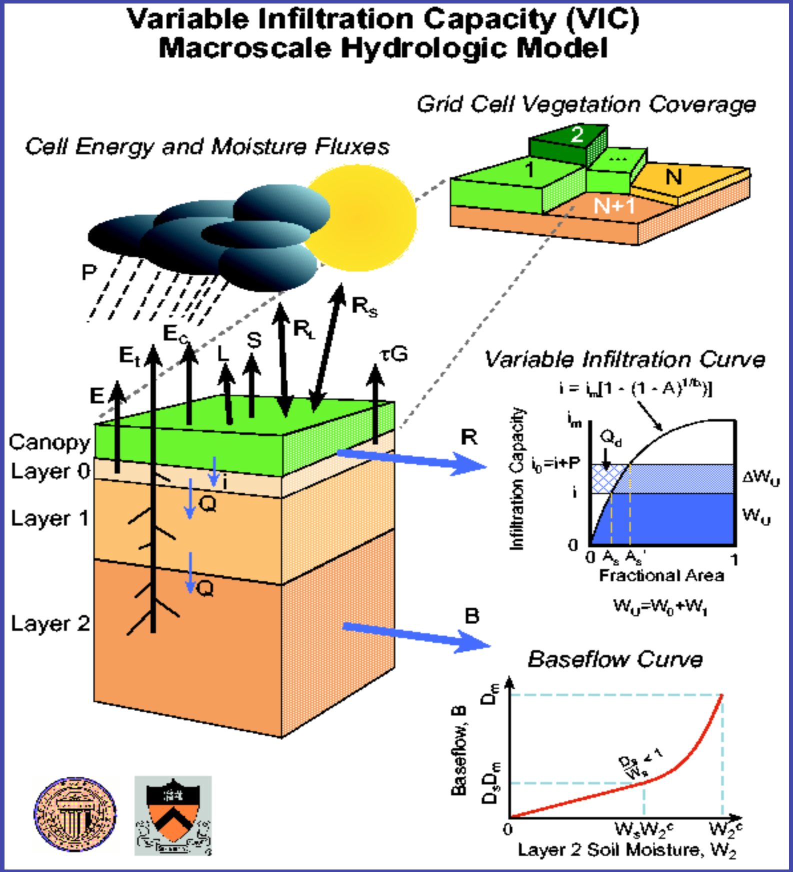
Wetland CH4 Emissions Rates
- Calibrate to in-situ observations

Lake CH4 Emissions Rates
- Try several values spanning in-situ observed rates

Input modeled emissions to atmospheric transport model and compare concentrations to AIRS satellite retrievals

Modeling Framework

- VIC hydrology model
  - Large, "flat" grid cells (e.g. 100x100 km)
  - Mosaic of land cover tiles
  - On hourly time step, simulate:
    - Soil T profile (and permafrost)
    - Water table depth Z_{WT}
    - NPP
    - Other hydrologic variables…
- Link to CH4 emissions model (Walter & Heimann 2000)

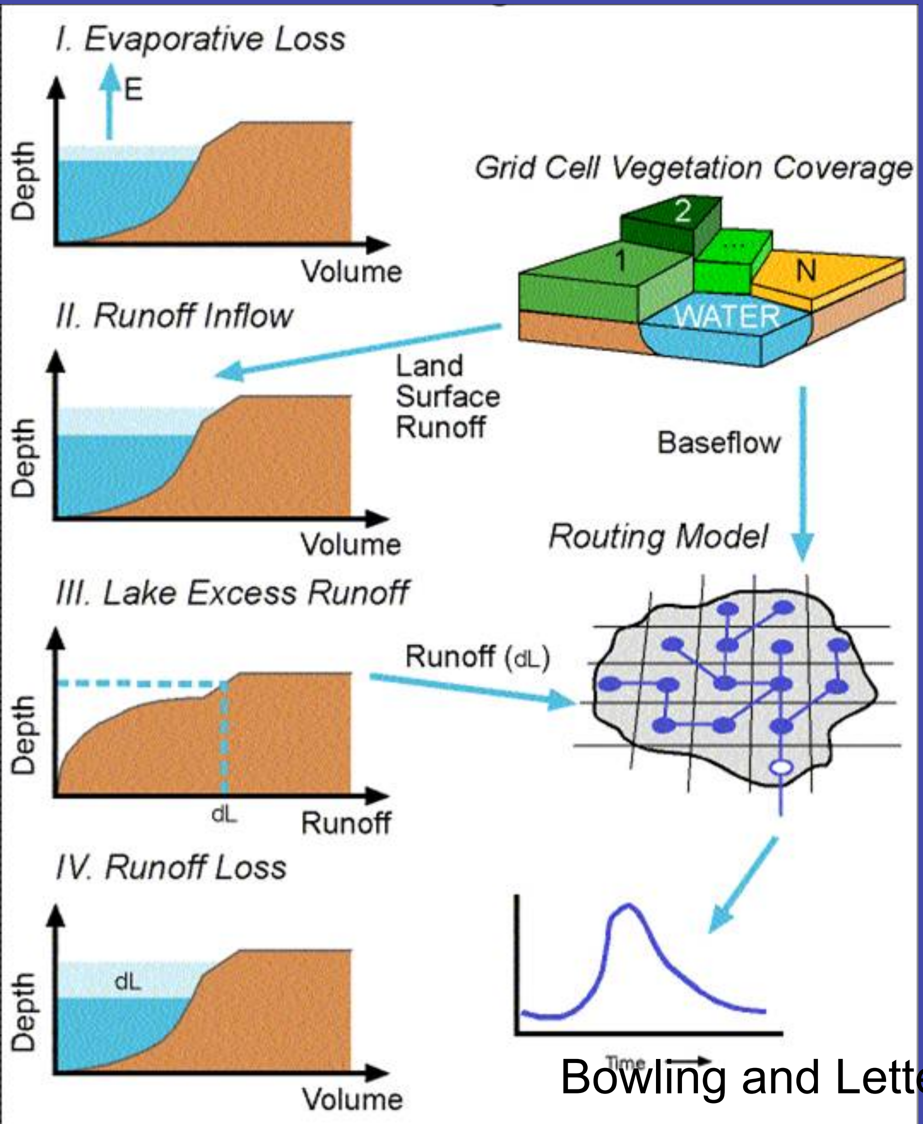


How to handle West Siberian features?

•Seasonal inundation: dynamic lake model

•Microtopography: distributed water table

VIC Dynamic Lake/Wetland Model



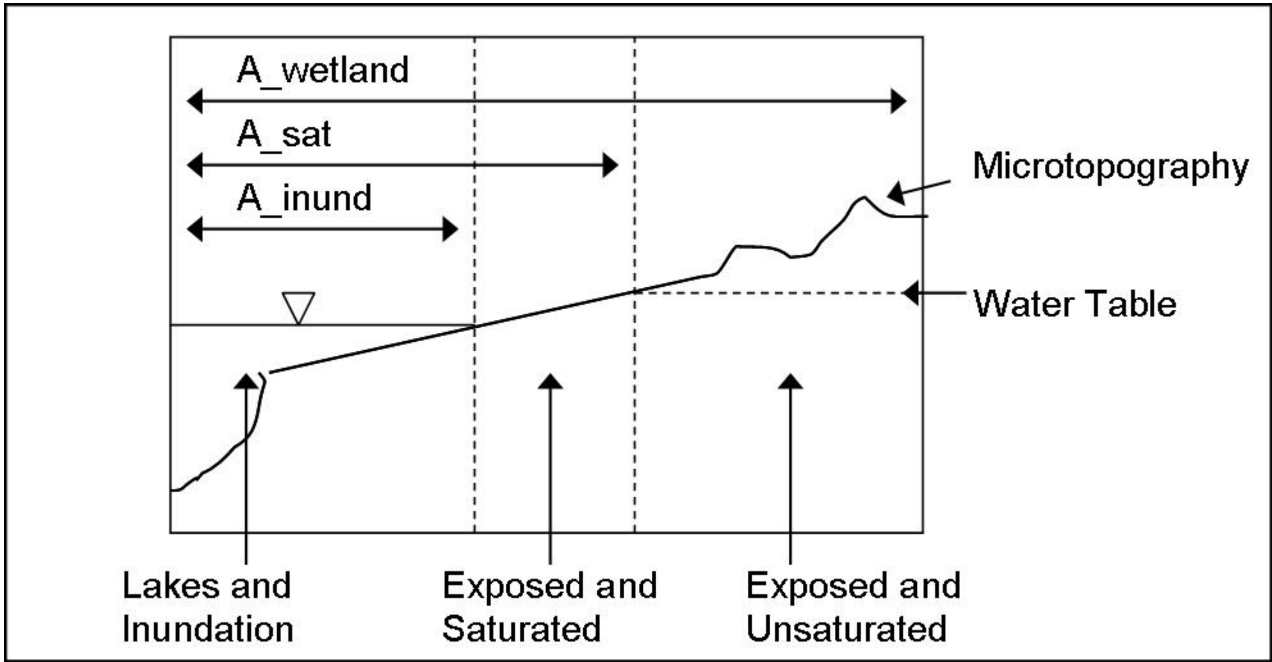
- Water & energy balance model
- Includes mixing, ice cover
- Dynamic area based on bathymetry
- Can flood surrounding wetlands based on topography

Bowling and Lettenmaier, 2010

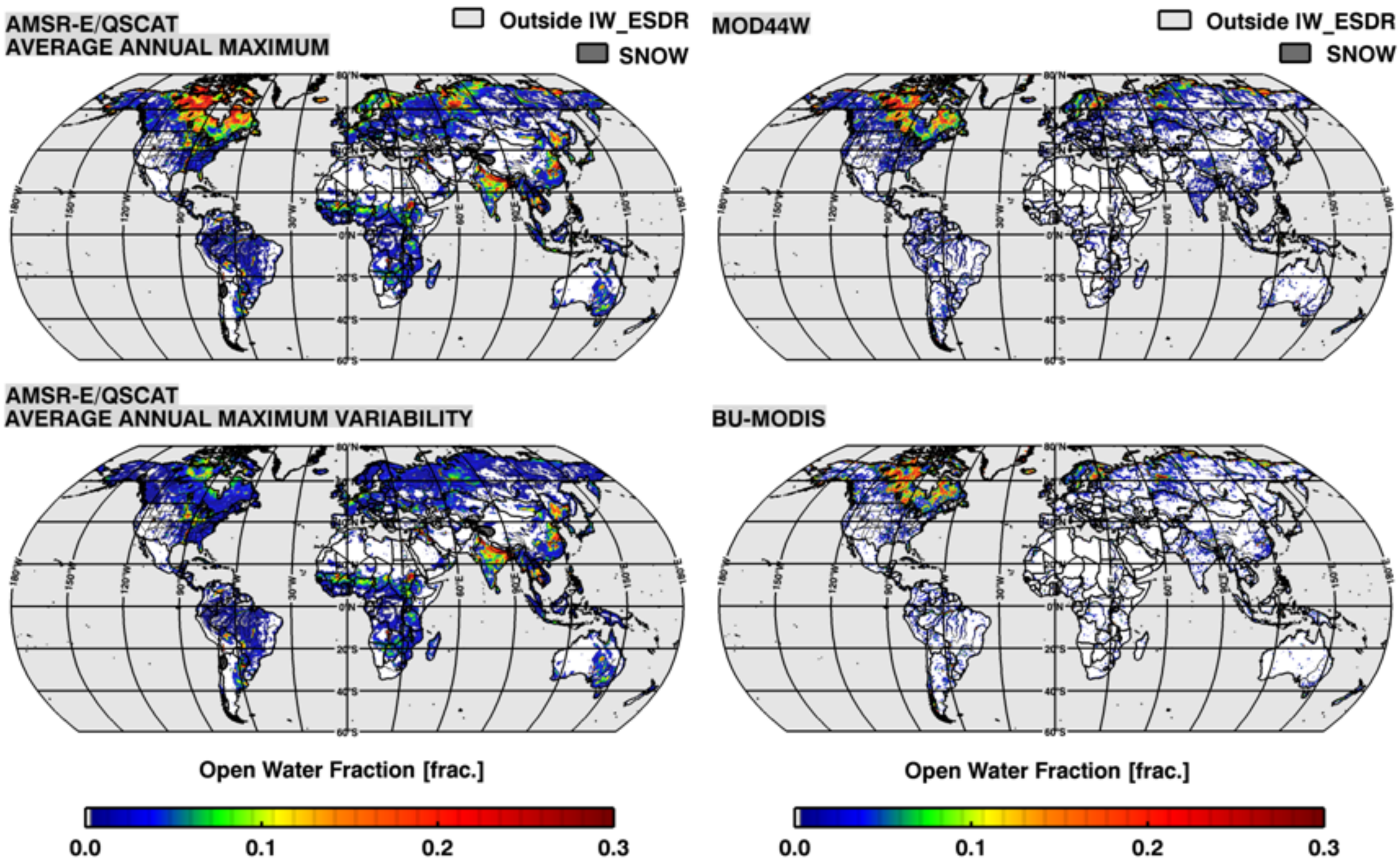
Lake/Wetland Tile

- Lake/wetland tile has prescribed area (peatlands: Sheng et al 2004; tundra: Bartalev et al 2003; "permanent" lakes: Lehner and Döll 2004)
- Time-varying areas of inundation and saturation within the tile
  - Drainage rate is calibrated to match inundation to passive microwave observations of Schroeder et al (2010)
- "permanent" lake area = subset of inundation
- Water table depth within exposed wetland is distributed between hollow and ridge

- Ridge area fraction calibrated
  - Saturated wetland generates runoff into inundated portion
- Peat soil properties in the wetlands
  - Peat depths from Sheng et al 2004



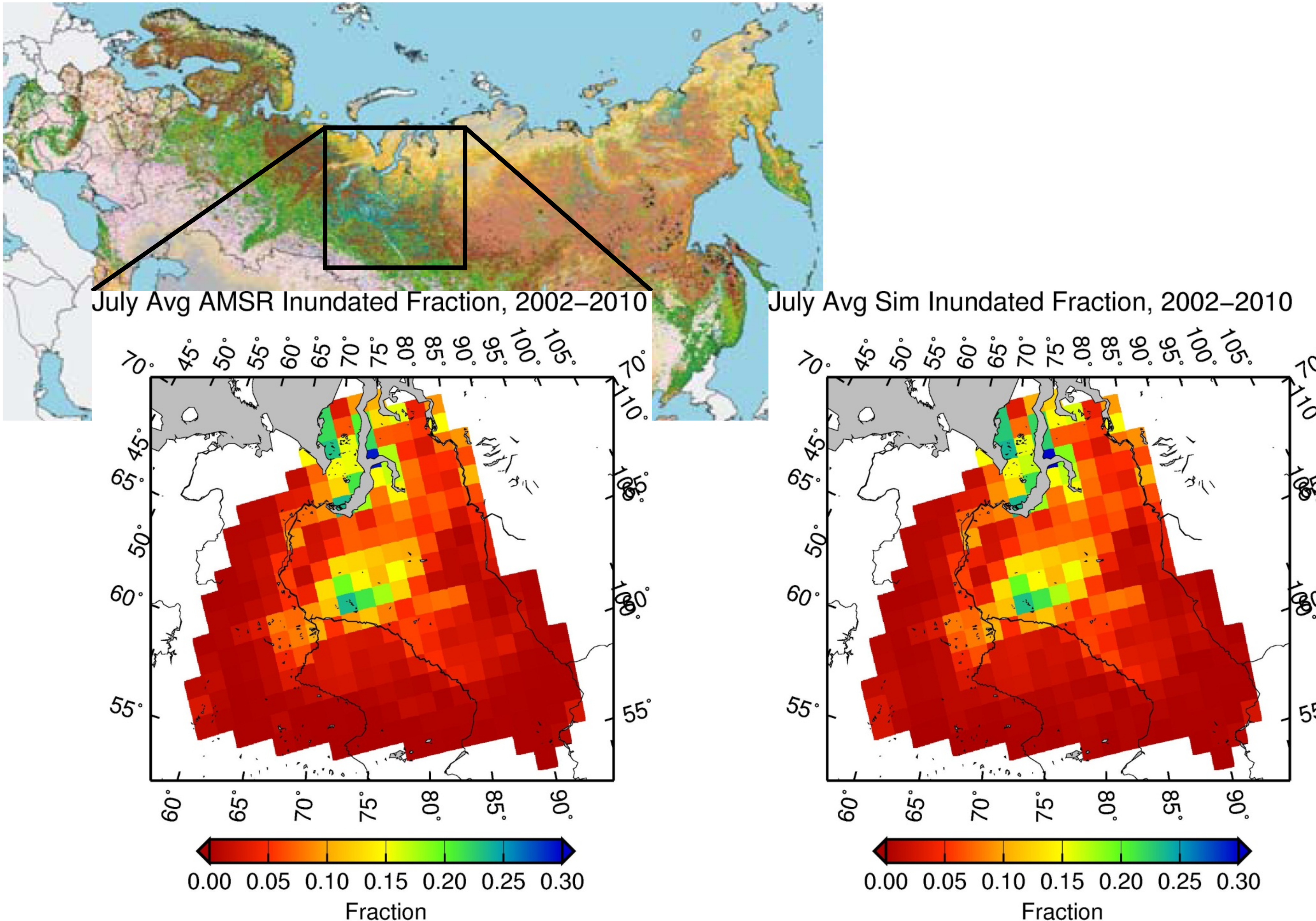
AMSR/QSCAT-Derived Inundation



- Daily, for snow-free days
- 2002-present
- 25km resolution

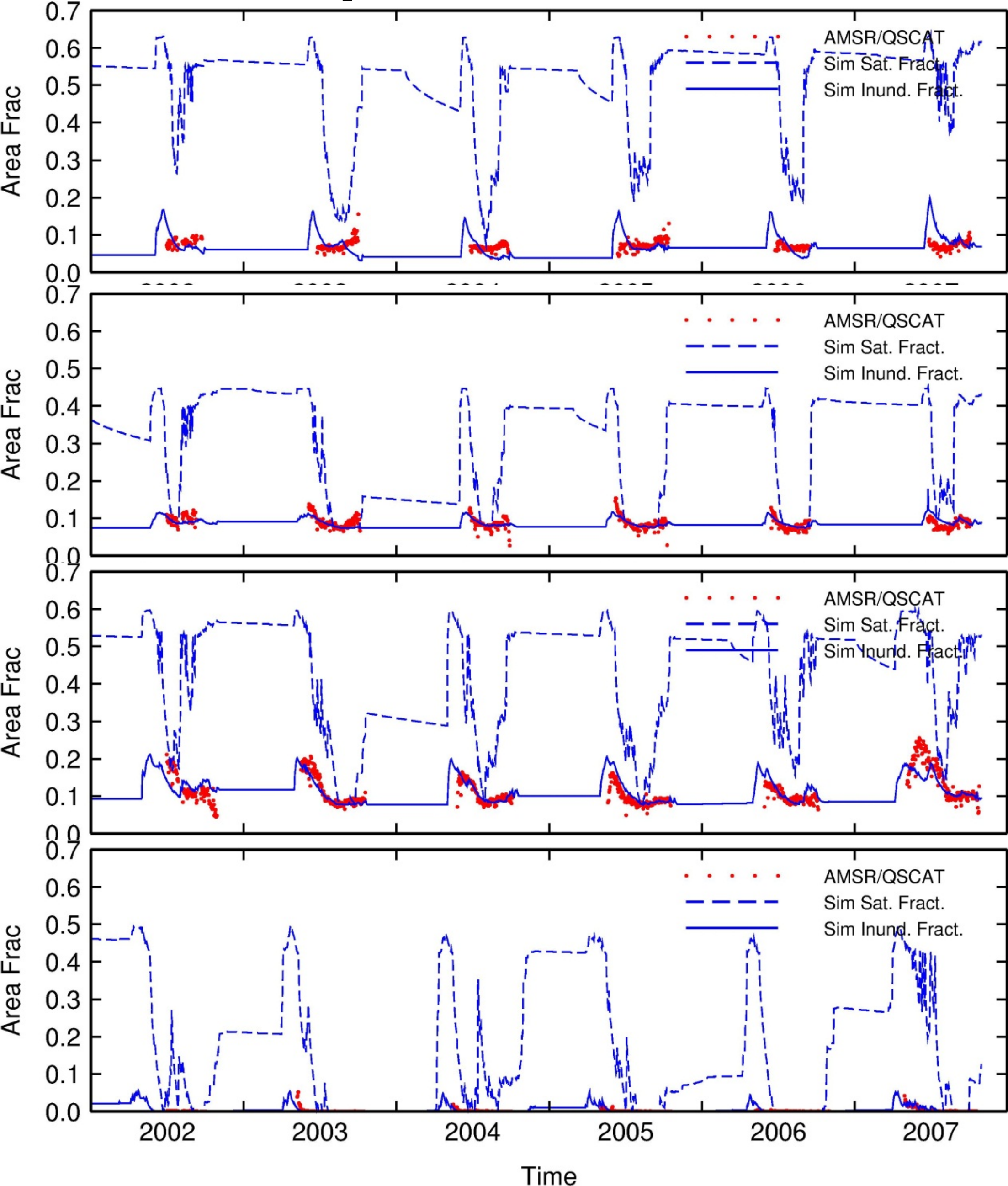
Courtesy R. Schroeder, NASA/JPL

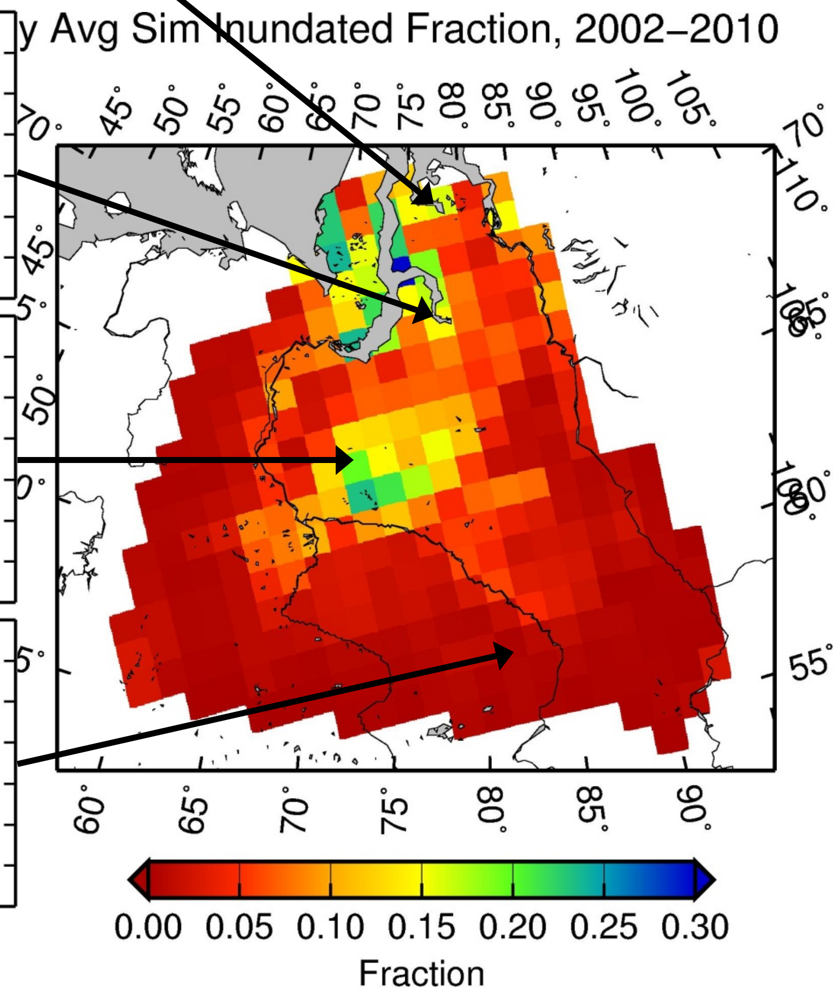
Model Comparison with AMSR/QSCAT



Comparison with AMSR/QSCAT

- In tundra zone, we do not capture seasonal cycle
- But inundated extent is roughly correct in July at peak of emissions





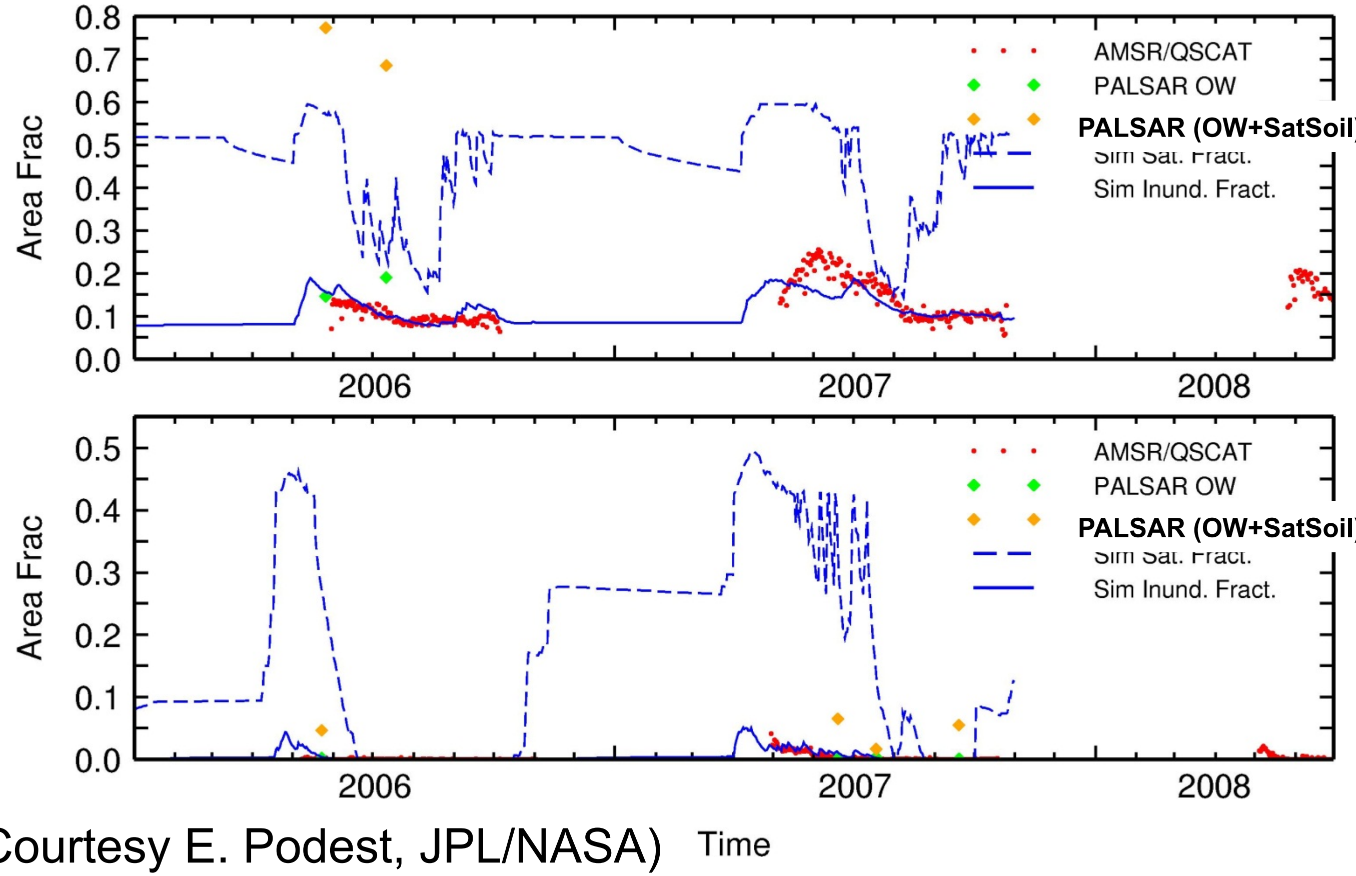
- This gives us inundated area
- How is modeled ***saturated area*** doing?

Comparison with PALSAR

Time series from two example locations

PALSAR OW = open water

PALSAR (OW +SatSoil) = total saturated area



(Courtesy E. Podest, JPL/NASA)

PALSAR OW agrees with AMSR inundation and VIC inundation

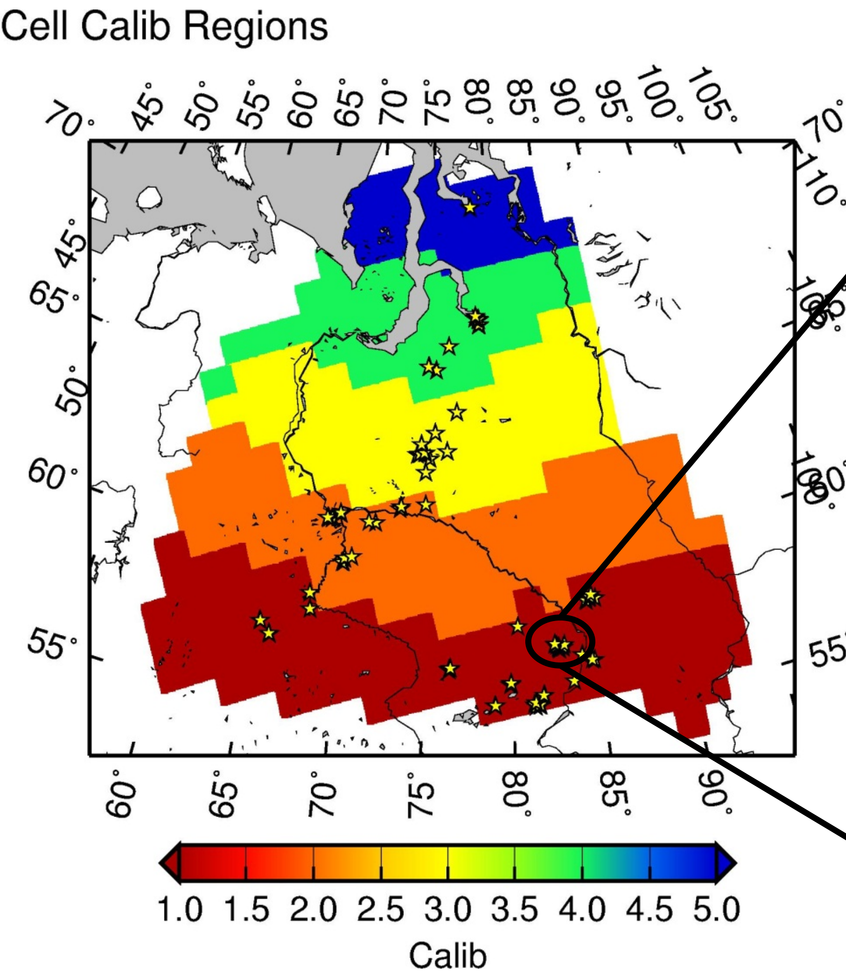
VIC saturated soil appears unbiased with respect to PALSAR (OW+SatSoil) but there is very large scatter

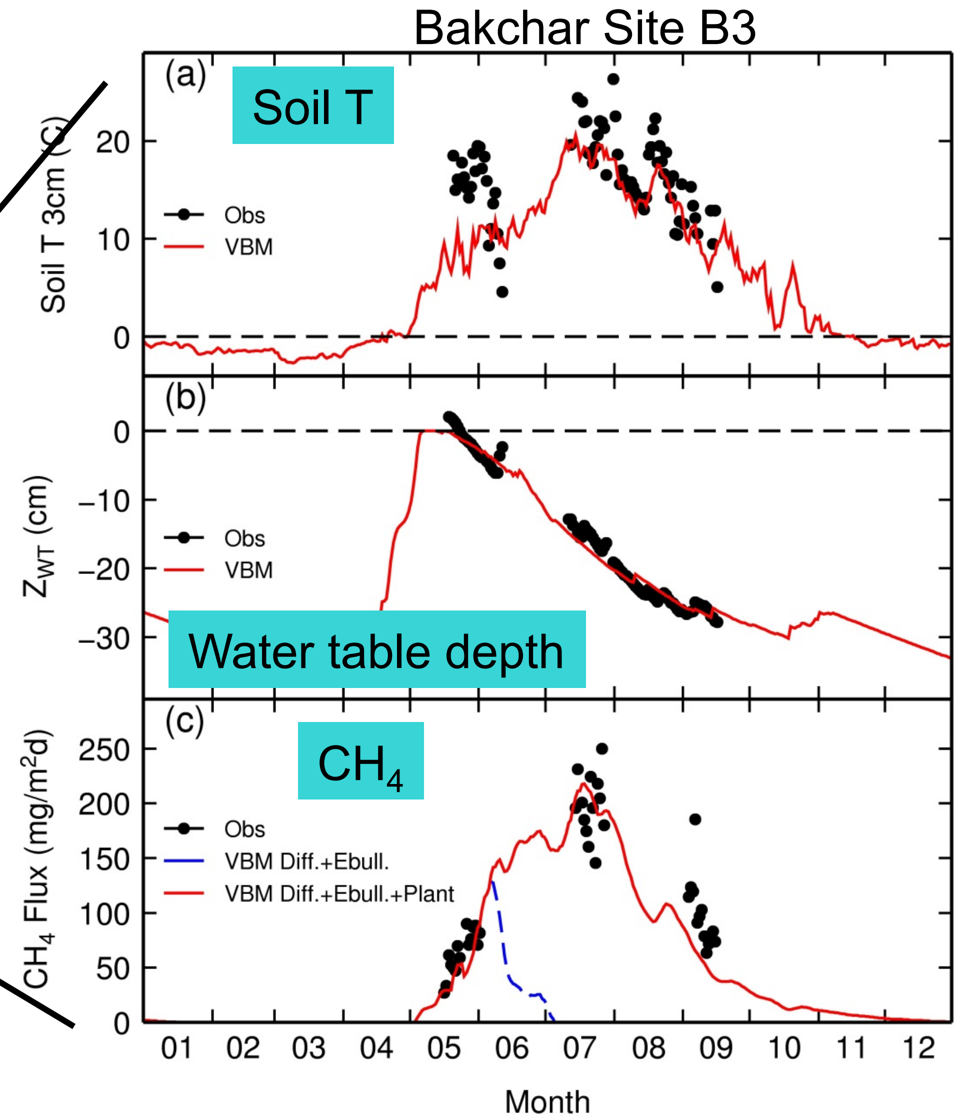
Methane Emissions

Model of Walter and Heimann (2000)

- Post-processing step
- Inputs = VIC outputs:
  - Soil T profile
  - NPP
  - Water table depths from 5 points on water table distribution:
    - Permanent inundation
    - Hollow average
    - Low, mid, high ridge
- Outputs = 5 CH_4 time series
- Does not account for pH, oxidation state
- Calibrated parameters:
  - Proportion of NPP that is labile C
  - Vertical profile of soil C
  - Rates of methanogenesis and oxidation
- Calibrated to match observations of Mikhail Glagolev (Moscow State University)

CH4 Emissions Calibration





Calibration Regions
Grouped by landcover, soil depth
50-100 observations in each

Friborg et al, 1999

Emissions Scenarios

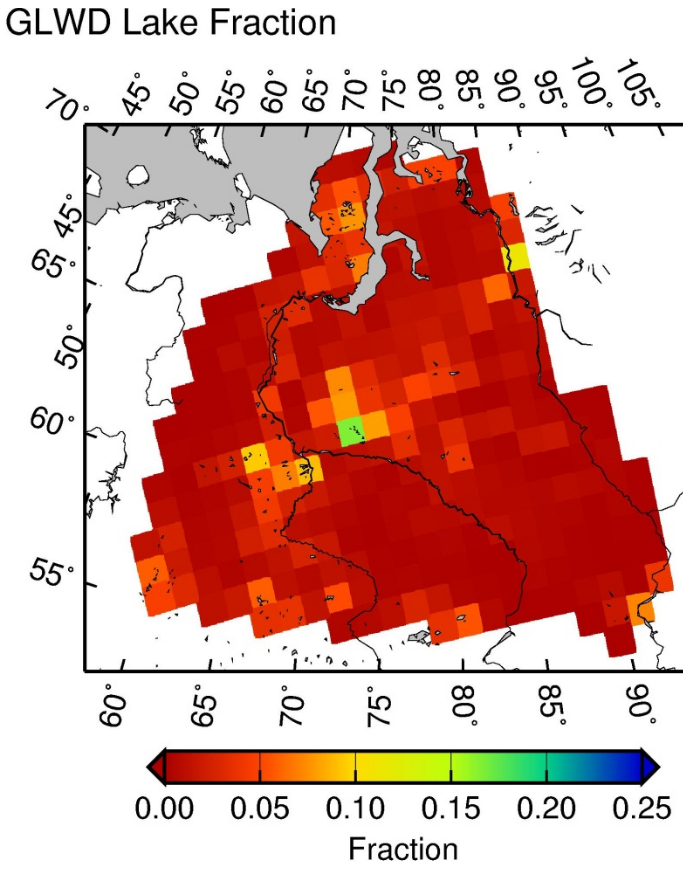
Bayesian Parameter Estimation indicates relatively much ***less uncertainty*** (+/- 30%) in estimates of wetland emissions than lake emissions (2 orders of magnitude)

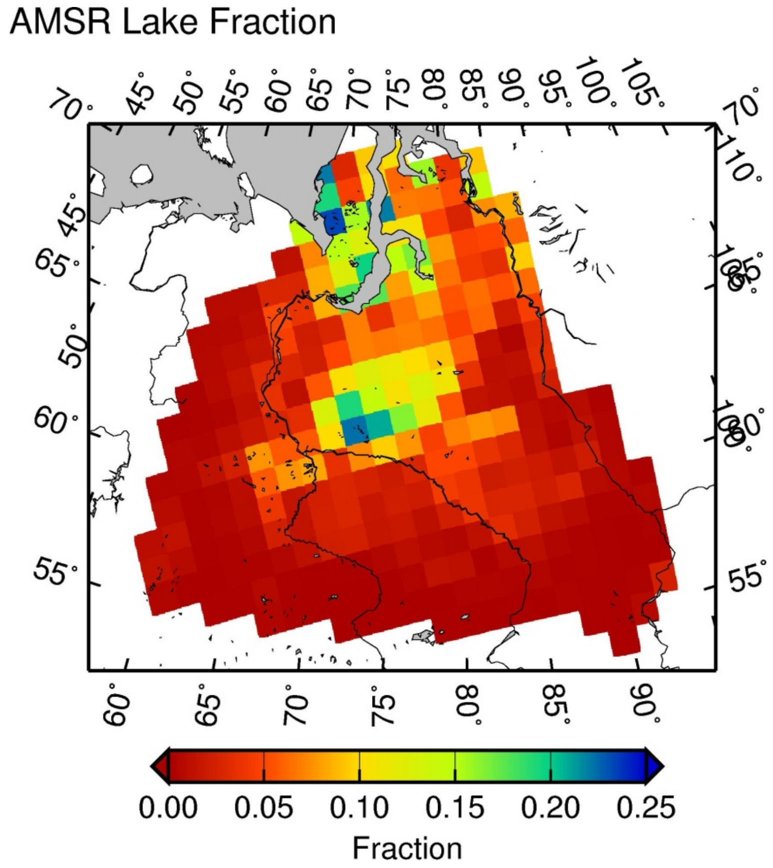
Therefore, the various possible emissions scenarios fall into 3 basic categories:

1. High Lake Emissions (500 gCH4/m2/day); GLWD Lake Area
2. High Lake Emissions (500 gCH4/m2/day); AMSR Lake Area
3. Low Lake Emissions (10 gCH4/m2/day)

Lake Areas

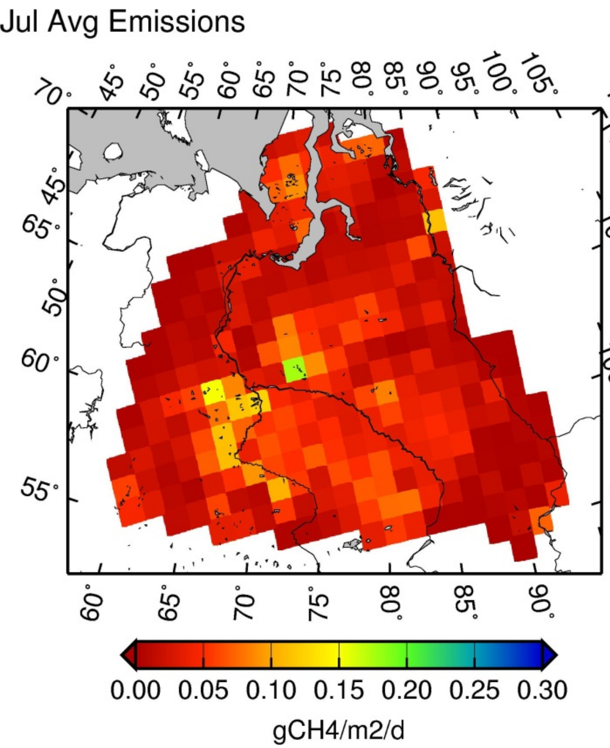
GLWD and AMSR-based lake areas differ in spatial pattern and in absolute extent





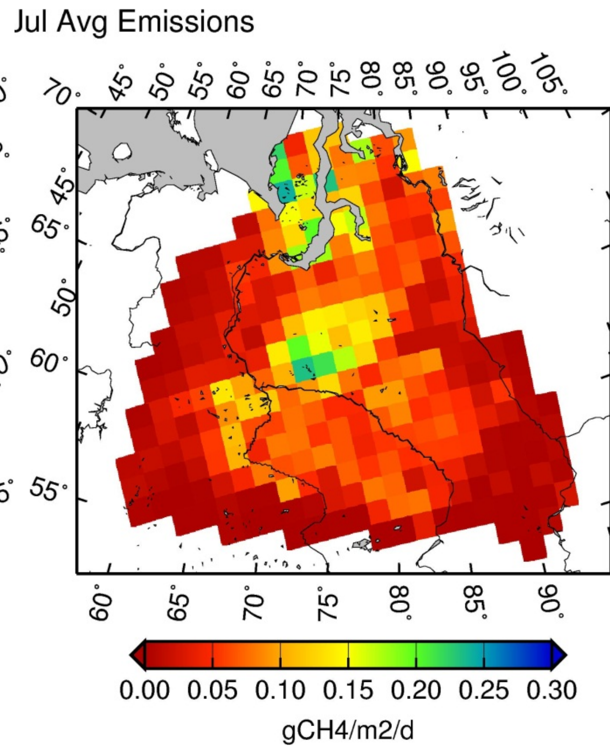
Emissions Scenarios

1. High Lake Emissions, GLWD Lake Area



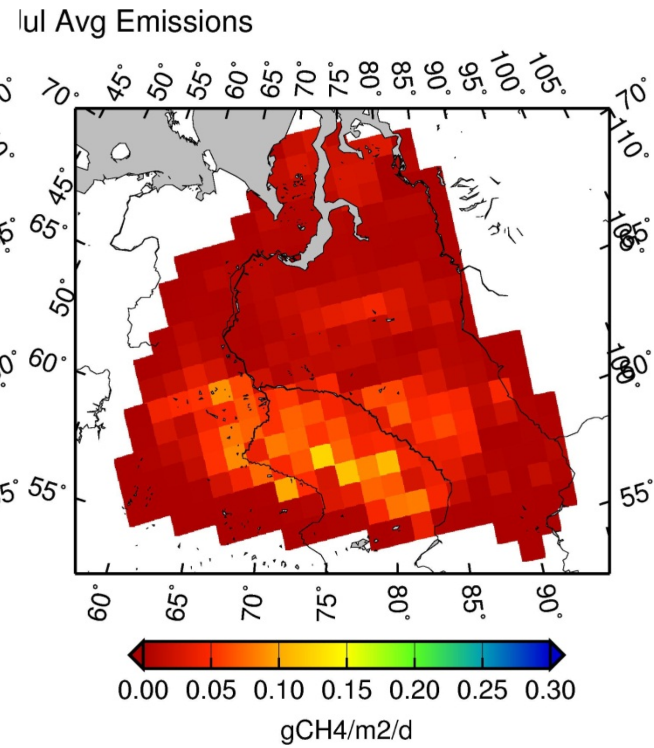
Annual emissions ~ 5.8 Tg CH4/year

2. High Lake Emissions, AMSR Lake Area



Annual emissions ~ 8.8 Tg CH4/year

3. Low Lake Emissions, Median Wetland Emissions



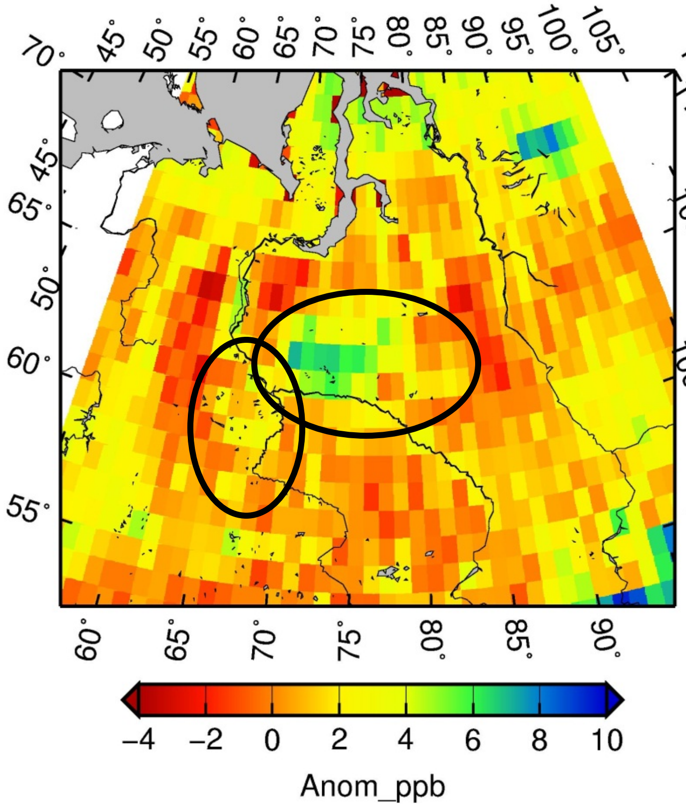
Annual emissions ~ 5.3 Tg CH4/year

Comparison to Satellite CH4

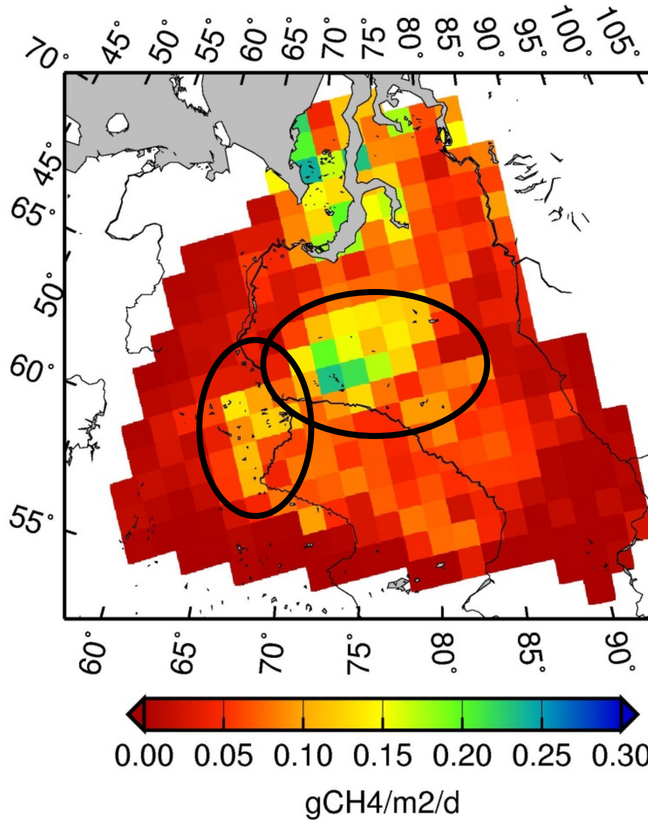
Routing through atmospheric transport model and comparison with AIRS is underway

But if we compare the spatial patterns of emissions with AIRS [CH4] zonal anomalies:

AIRS CH4 Zonal Anomalies, JJA 2003–2010



Jul Avg Emissions



- Scenario #2 (8.8 TgCH4/year) seems most plausible spatial distribution
- This implies lake emissions around 500 gCH4/m2/day
- Interpret with caution, since [CH4] affected by advection and oxidation in atmosphere

Conclusions

- Using a combination of models and remote sensing, it is possible to constrain large-scale lake and wetland methane emissions
  - Wetland emissions better-constrained than lake emissions (less freedom to vary)
  - Therefore, lake emissions can be "tuned" to reproduce observed spatial pattern of emissions
- Lake emissions rates at the higher end of observed range (~ 500 gCH4/m2/day) seem likely
  - 30-60% of emissions in W. Siberia
- Lake areas may lie between GLWD and AMSR annual minimum; AMSR seems closer to truth
- Total CH4 emissions from W. Siberia could range from 5-9 Tg CH4/year
  - Comparable to estimates from other studies, but on the high side
- PALSAR classification helps constrain saturated soil extent, but we need ***much more*** of it, both in ***time*** and ***space***

Example 2: Seasonal hydrologic prediction

The potential for improved seasonal hydrologic forecasts in the western U.S.

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Department of Civil and Environmental Engineering

Outline

1. **Relative importance of hydrologic initial conditions and weather/climate forecast skill.**
2. **The contribution of medium range weather forecasts (~2 weeks) to seasonal hydrologic forecast skill.**
3. **Hydrologic data assimilation to improve hydrologic forecasts at medium range to seasonal lead times.**
4. **Potential medium-range to seasonal climate forecast skill**

1. Relative importance of hydrologic initial conditions and weather/climate forecast skill

Koster et al., 2010 – MAMJJ r^2 with observations

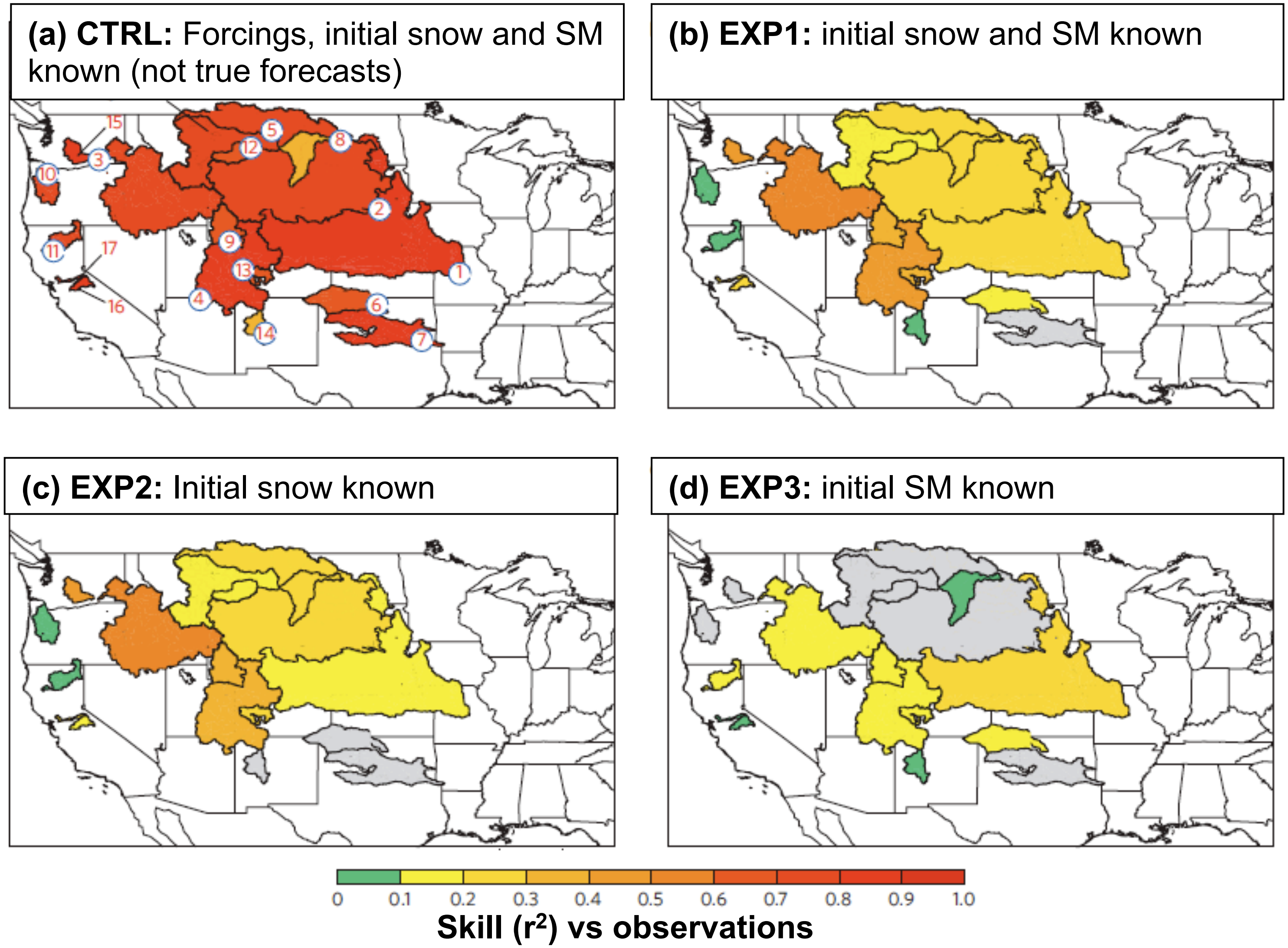


Fig. 1: Streamflow skill levels (i.e. r^2 between MAMJJ total streamflows from simulations and corresponding naturalized measurements) achieved in the simulation experiments. The grey colouring indicates skill not significantly different from zero at the 95% confidence level

Mahanama et al., 2011 – 3-month 0-lead forecasts

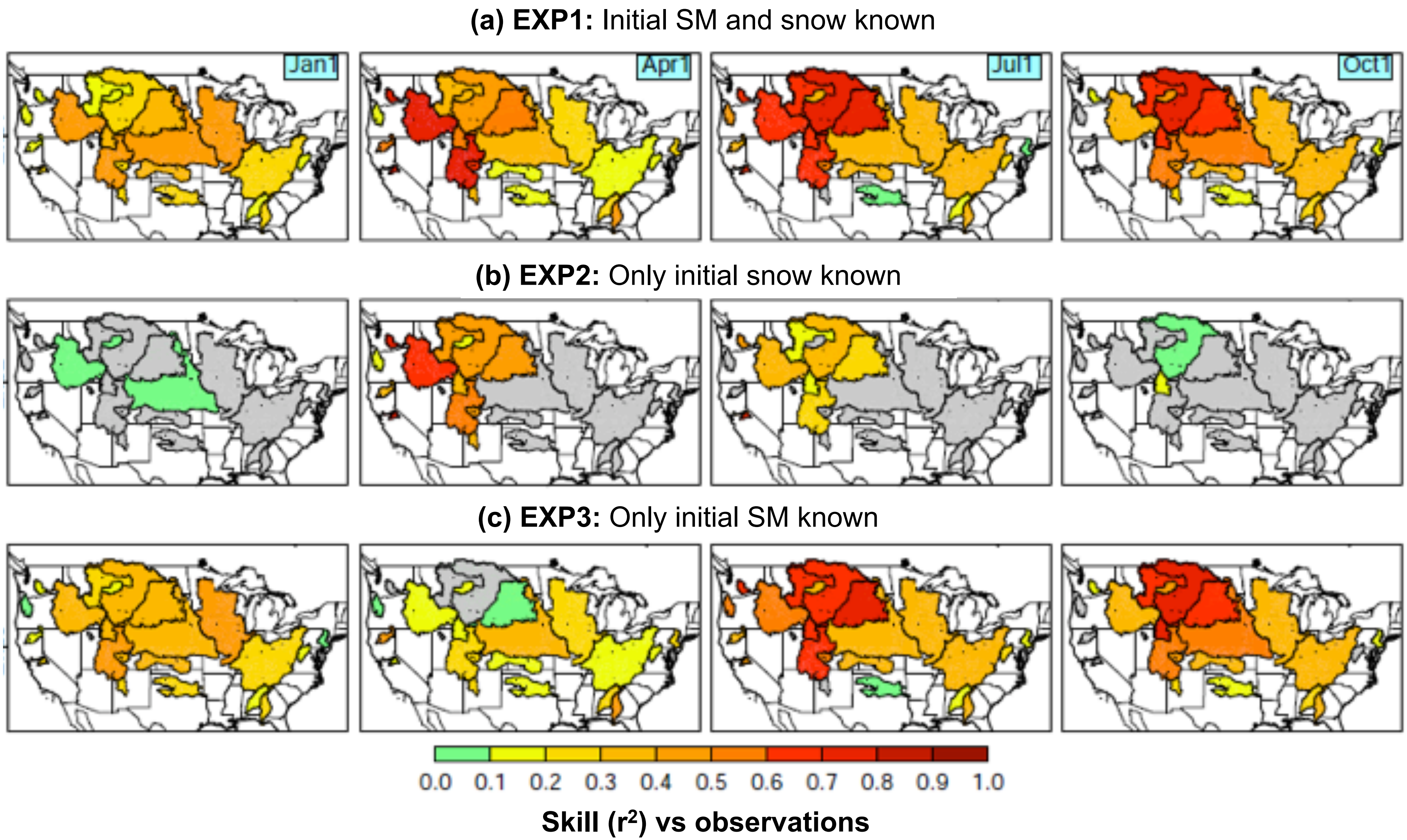
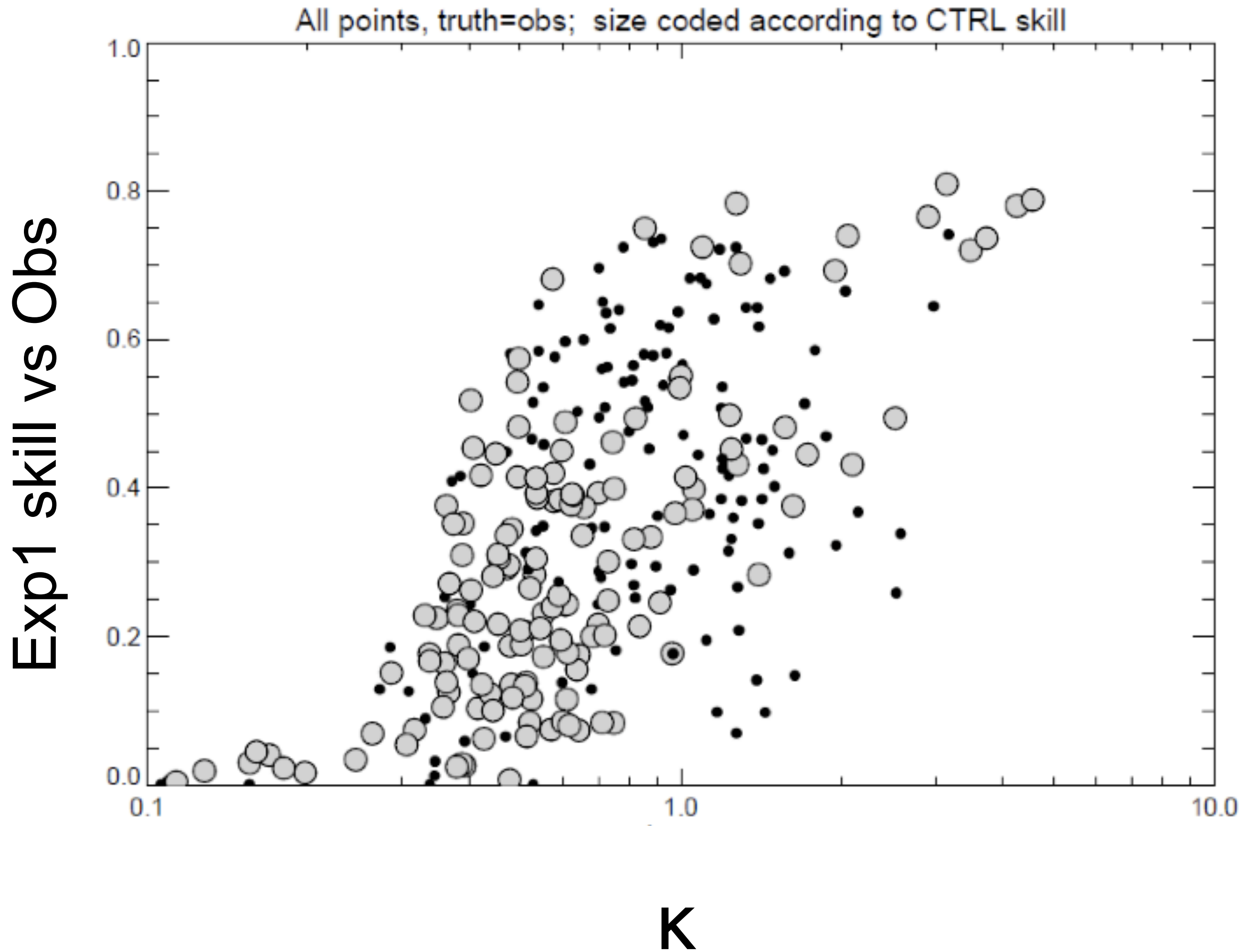


Fig. 2. Skill (r^2) of multi-model ensemble 3-month streamflow forecasts at 0-month lead for four start dates (columns) and the three experiments (rows). Gray shading indicates that skill levels are not significant at the 95% level.

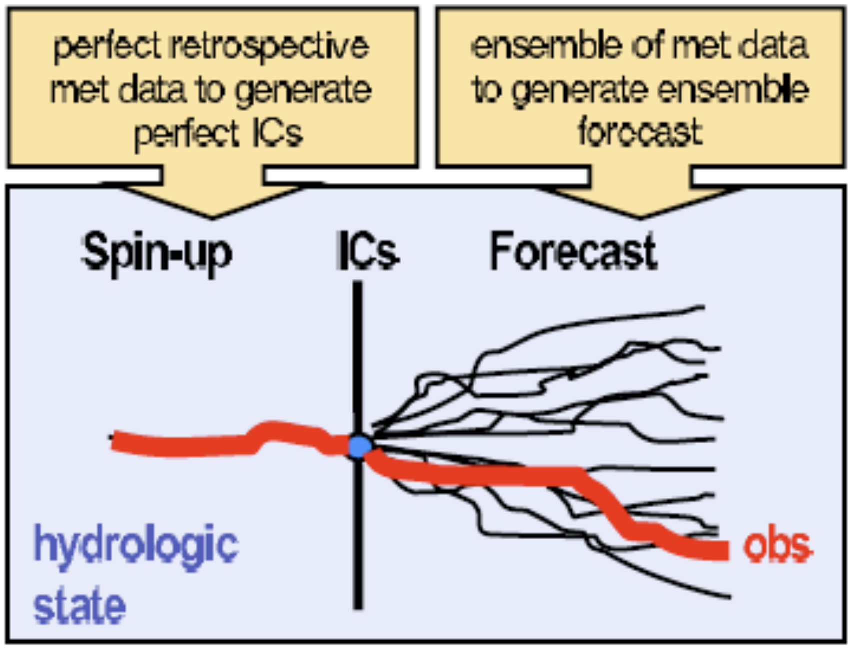
Mahanama et al., 2011



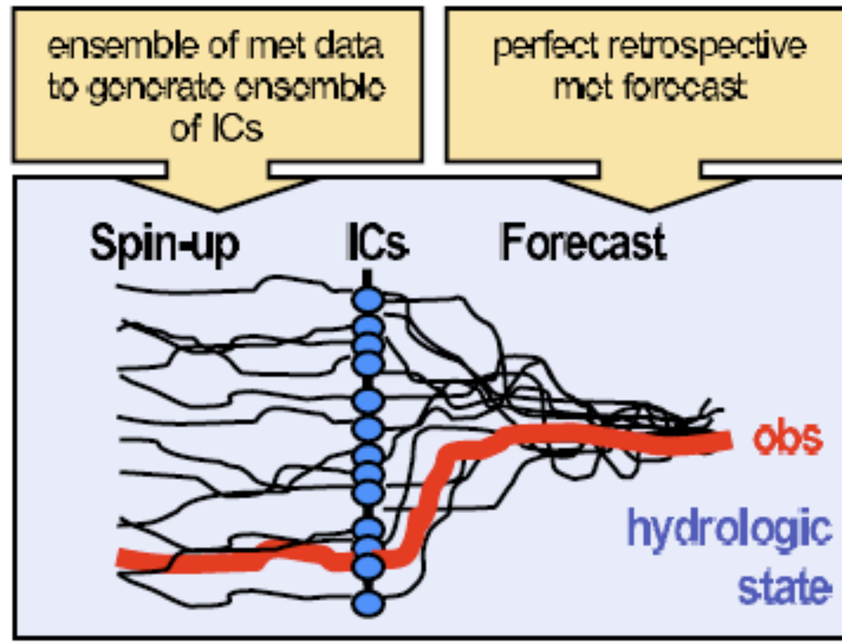
κ = σ(initial storage)/σ(forecast period precipitation)

Alternative approach – ESP vs RevESP

Experiment 1: Ensemble Streamflow Prediction (ESP)



Experiment 2: Reverse-ESP (*rev*ESP)



Shukla and Lettenmaier, 2011, HESS.

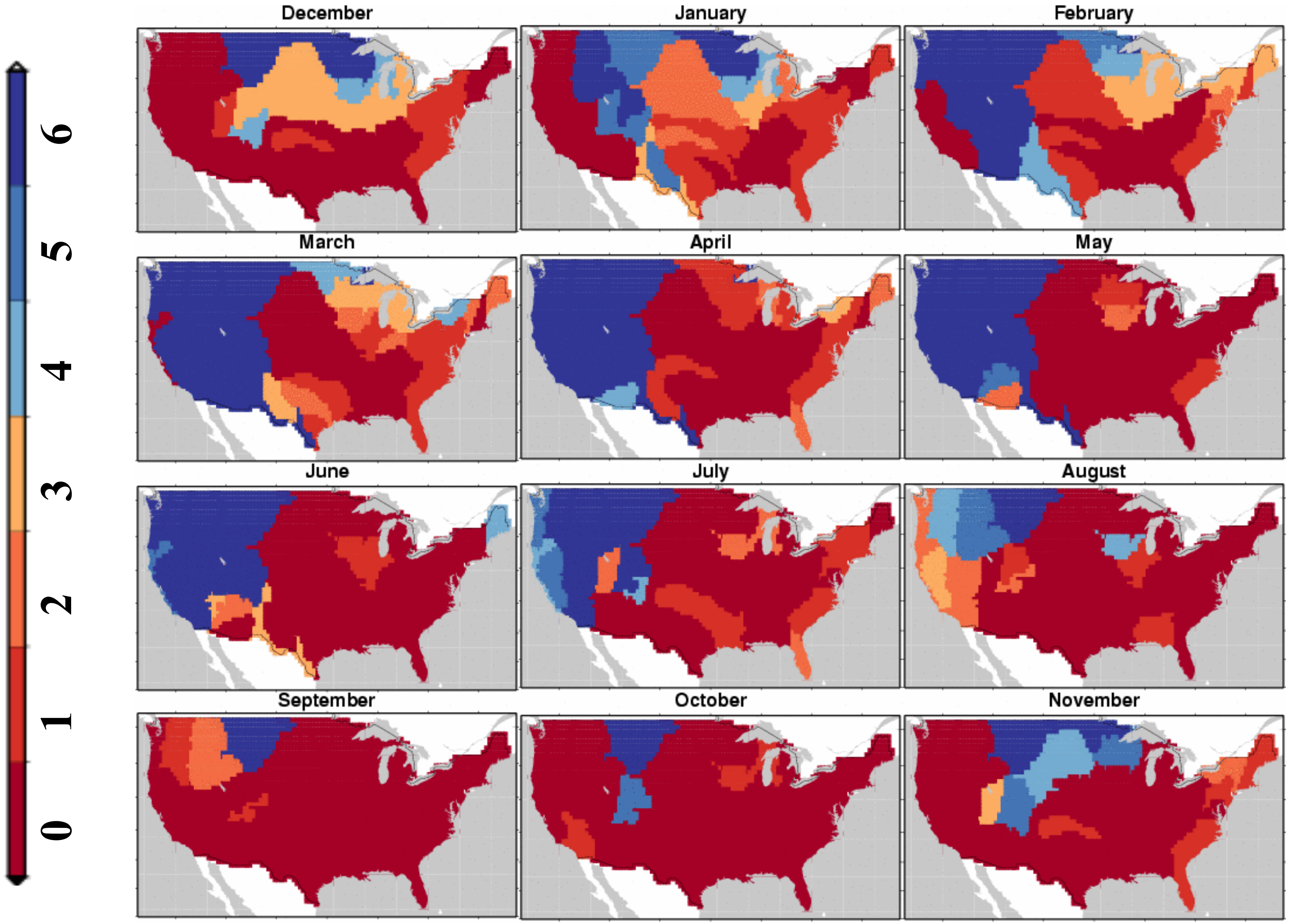
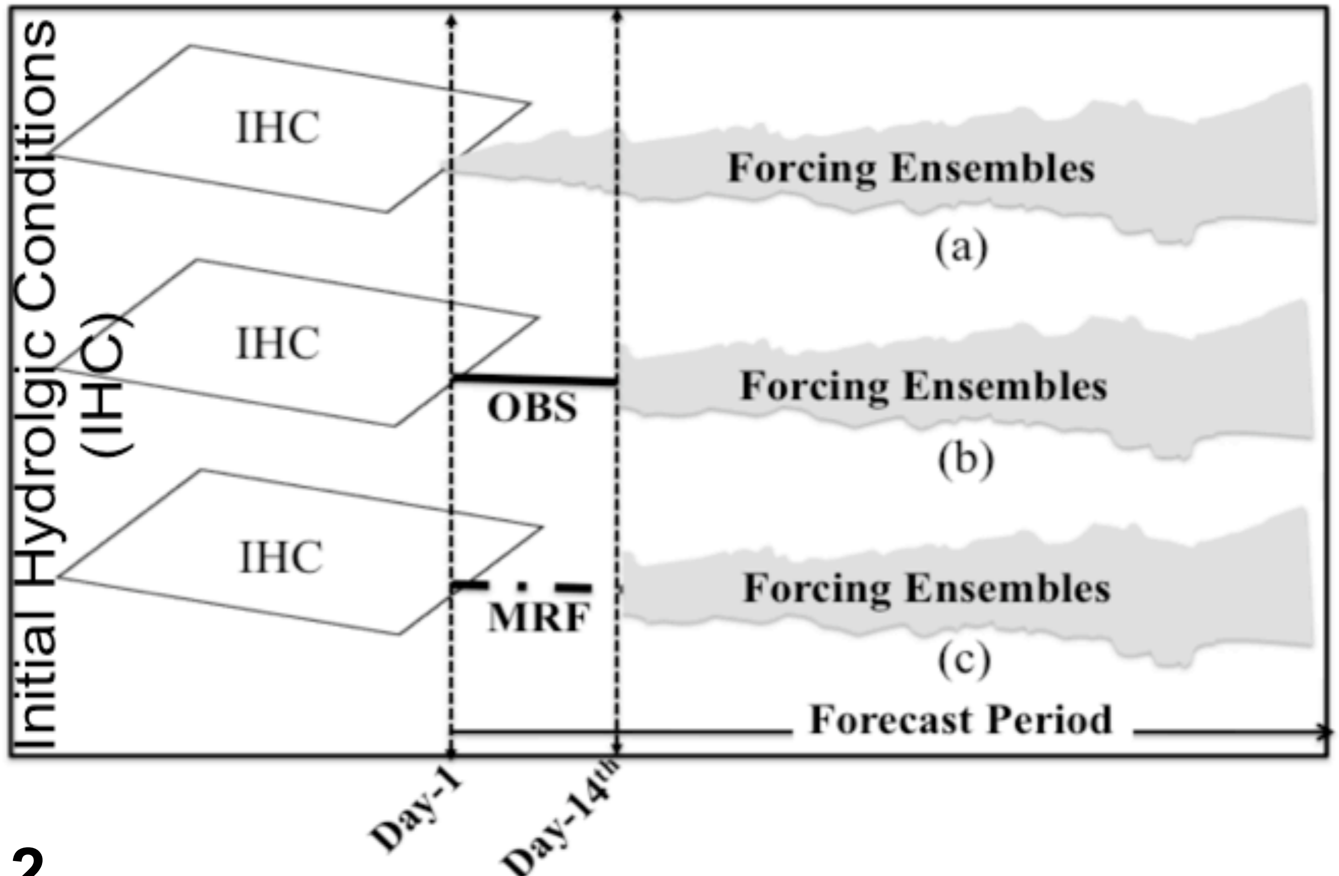


Fig. 5: Plot of the maximum lead (in months) at which RMSE Ratio [RMSE(ESP)/RMSE(revESP)] is less than 1, for ***cumulative runoff forecasts***, initialized on the beginning of each month.

2. The contribution of medium range weather forecasts (1-2 weeks at most) to seasonal hydrologic forecast skill.

Experimental Setup

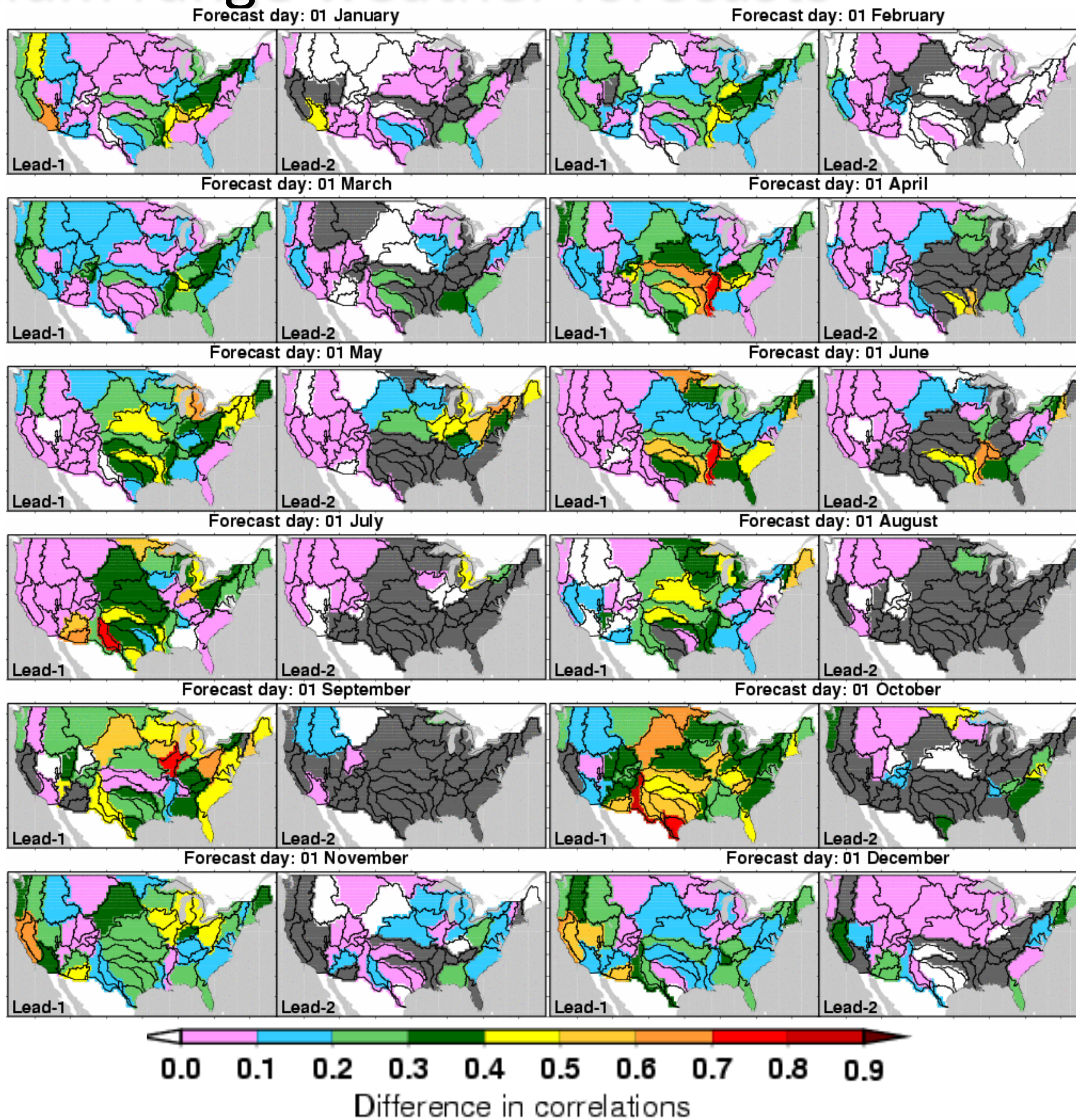
Fig. 7 : Schematic diagram showing the framework of experiment
(a) Experiment-1 (*ESP*)
(b) Experiment-2 (*OBS_Merged_ESP*)
(c) Experiment-3 (*MRF_Merged_ESP*).



Shukla et al., 2012, HESS (*in review*)

Potential Improvement in seasonal *runoff* forecast skill due to use of medium range weather forecasts

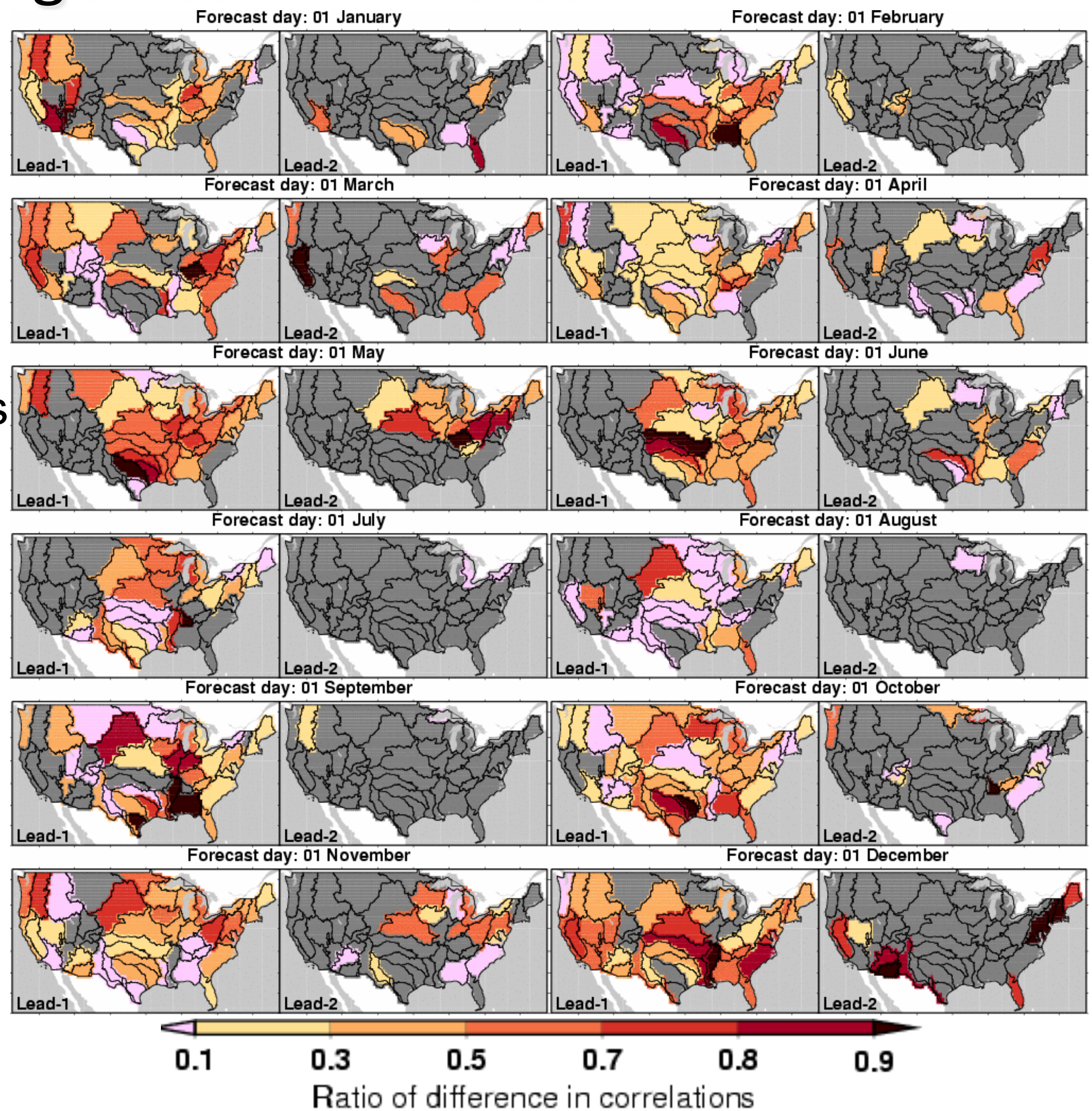
Fig. 8: Potential improvement in runoff forecast skills (*i.e. difference between the skill of OBS_MERGED_ESP and ESP*) at leads 1-2 months. (Dark grey color shows the sub-regions where the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)



Shukla et al., 2012, HESS (*in review*)

Actual Improvement in seasonal *runoff* forecast skill due to use of medium range weather forecasts

Fig. 9: The ratio of actual improvement and potential improvement in baseline runoff forecast skill at leads 1-2 months. (Dark grey color shows the sub-regions where either the potential improvement in skill is < 0.1 or the skill of *OBS_Merged_ESP* is not significant at 95% significance level.)



Shukla et al., 2012, HESS (*in review*)

3. The potential for hydrologic data assimilation

Assimilation of snow cover extent (MODIS)

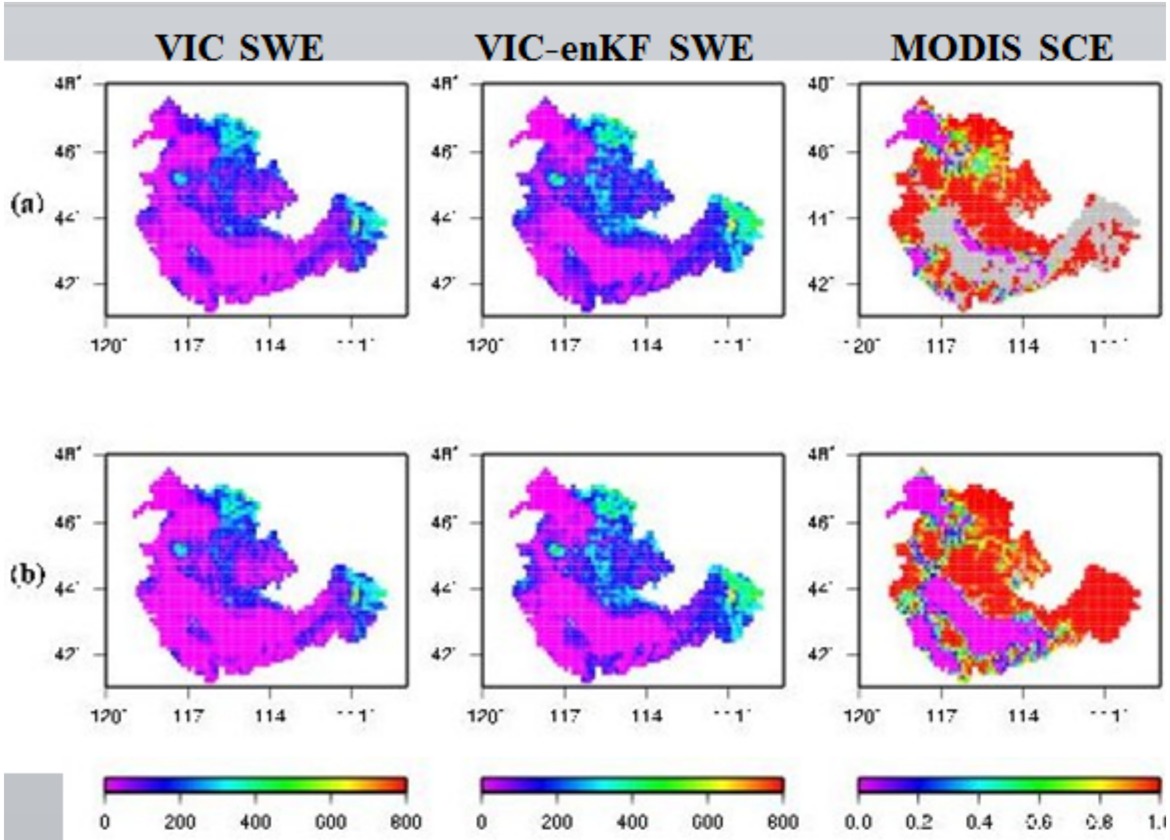
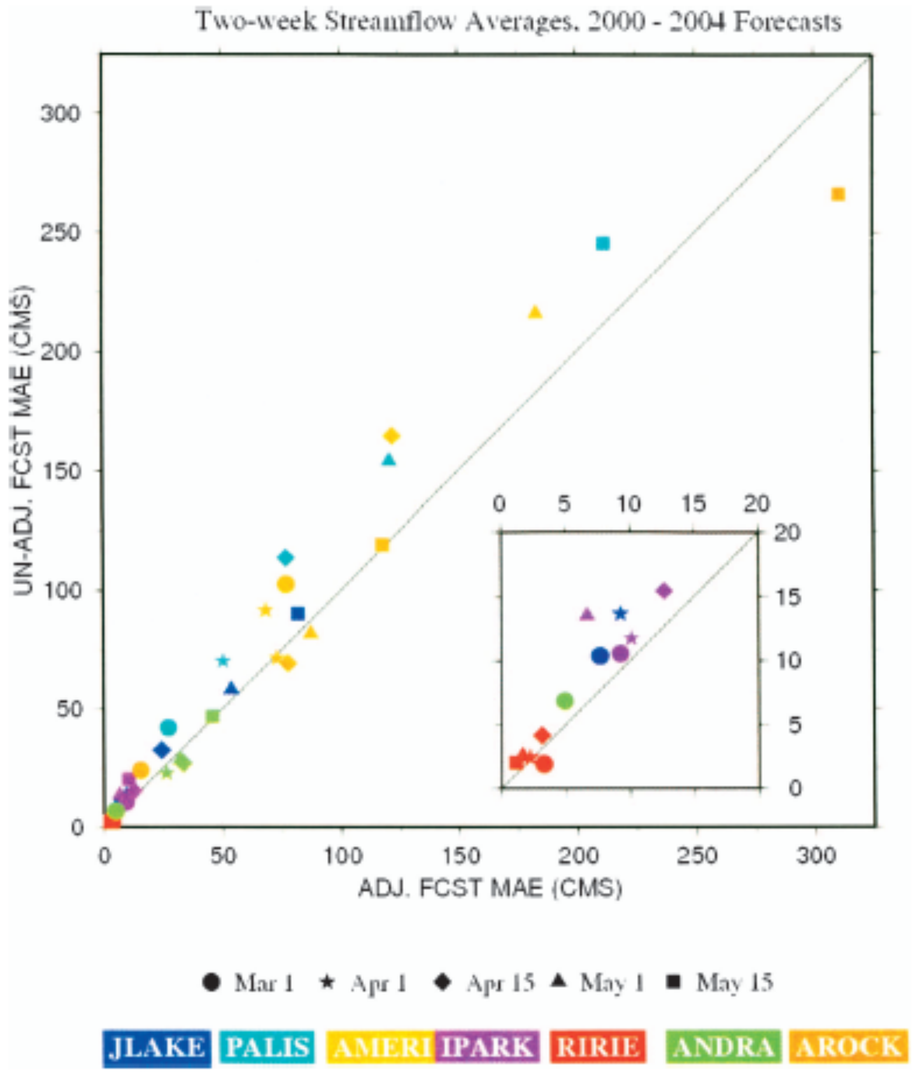


Figure 6. Snapshots of simulated SWE without assimilation (VIC), with assimilation of MODIS SCE data (VIC-enKF), and observed SCE (MODIS) for two dates in winter of 2001.

Visual courtesy Kostas Andreadis

Two-week adjusted (assimilated) and unadjusted forecast MAEs, Snake River sub-basins with MODIS updating



from McGuire et al., 2006

Conclusions

1. IHCs can dominate hydrologic skill for up to several months, depending on location and forecast initialization date. This is a relatively easy source of skill to exploit.
2. Medium range (~15 days; "weather") forecast skill can have a substantial effect on seasonal hydrologic forecast skill, however actual (based on real weather forecast skill) vs ideal reduces the potential considerably
3. Under conditions where IC dominates hydrologic skill, data assimilation (snow, soil moisture) is a viable approach to increasing forecast skill. Furthermore, there appears to be substantial potential for soil moisture assimilation over much of the country.
4. In most of the extratropics, climate model forecast skill that is exploitable for hydrologic predictions is modest at best.

Example 3: Hydrologic applications of satellite altimetry

Benefits of satellite altimetry for transboundary basins

S. Biancamaria [1,2], F. Hossain [3], D. P. Lettenmaier [4], N. Pourthié [2] and C. Lion [1,2]

[1] LEGOS, Toulouse, France

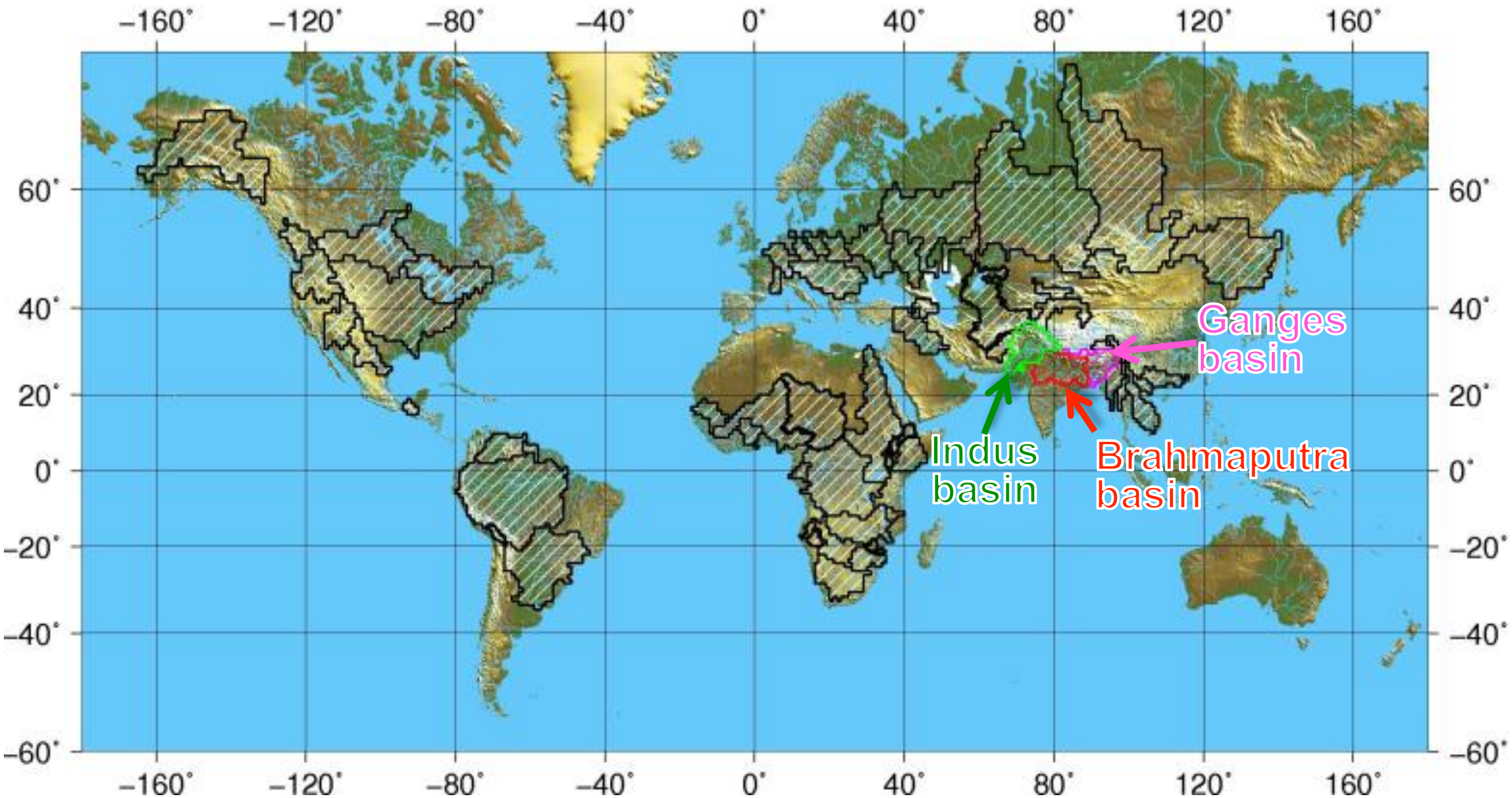
[2] CNES, Toulouse, France

[3] CEE, Tennessee Tech University, Cookeville, TN, USA

[4] CEE, University of Washington, Seattle, WA, USA

Transboundary basins

- 256 river basins are shared among 2 or more countries (Wolf et al., 1999) = 45% land surfaces



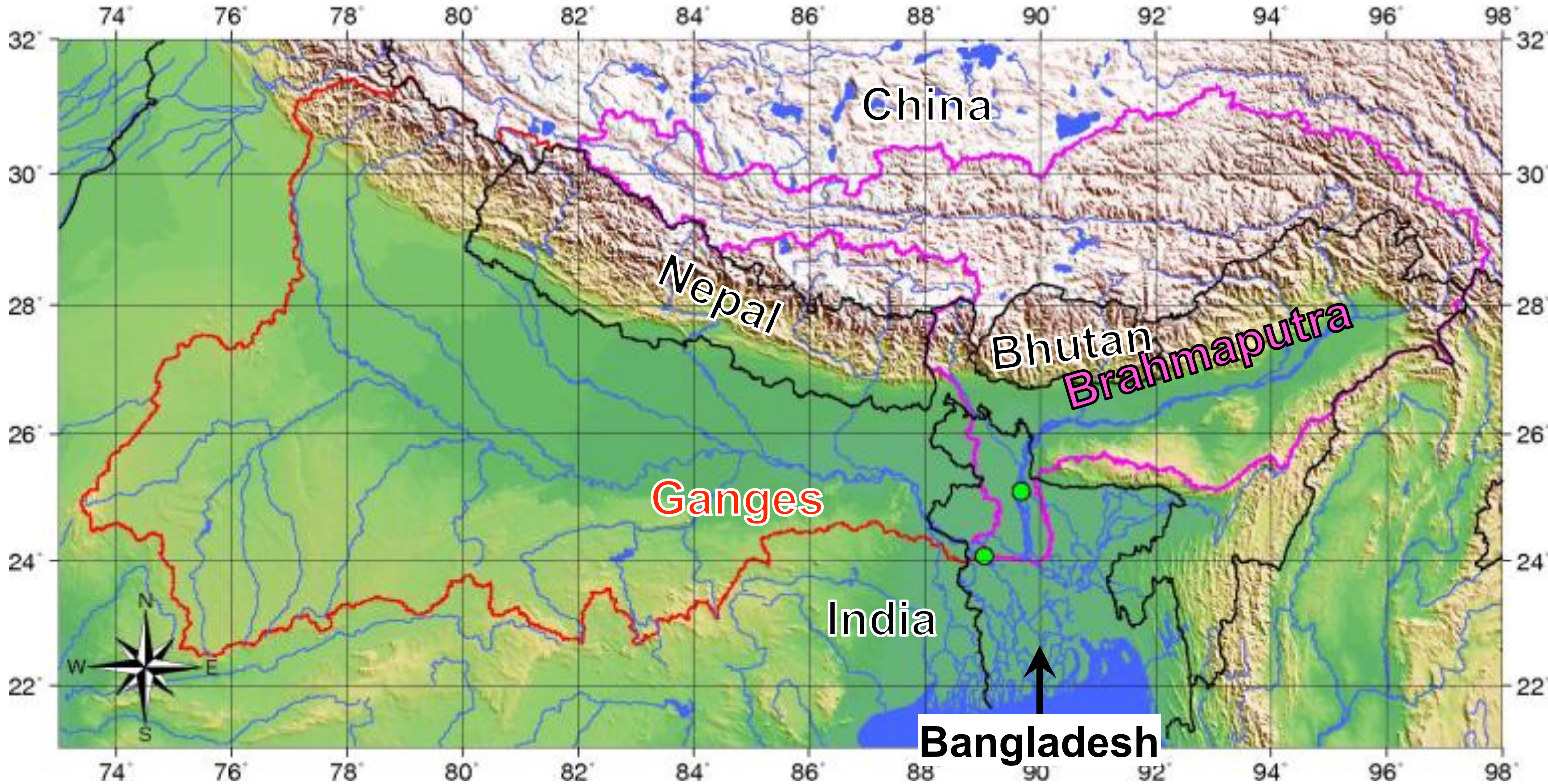
Outline

1. Forecasting Brahmaputra/Ganges water elevations using satellite altimetry

2. Monitoring Indus reservoirs with SWOT

Brahmaputra and Ganges basins

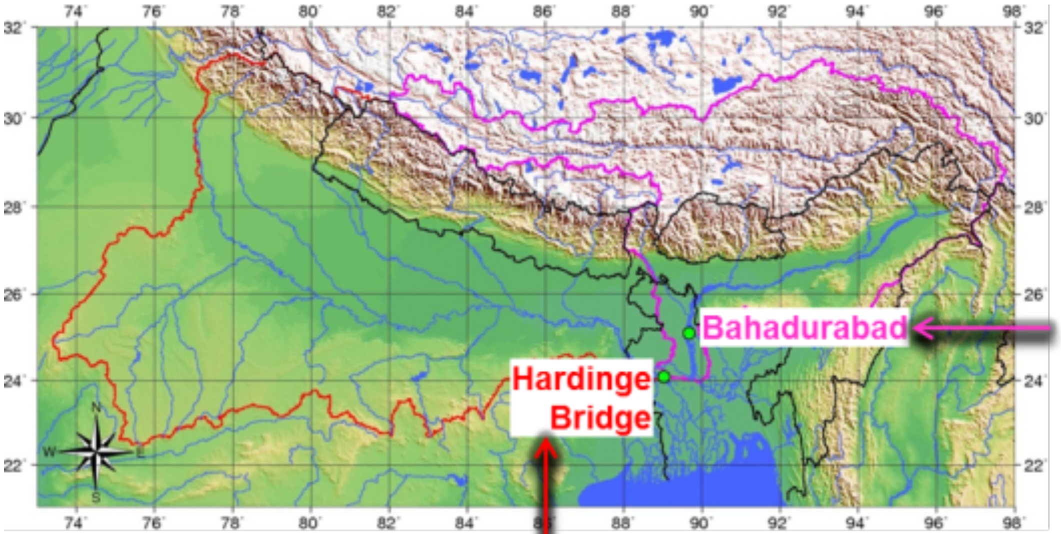
- Brahmaputra: drainage area=574,000km^2; population=30 Millions; unmanaged.
- Ganges: drainage area=1,065,000km^2; population=500 Millions; 34 dams/diversions.



Issue

- 90% of water flowing in Bangladesh comes from India.
- No India/Bangladesh real time data sharing.
- Using in-situ measurements at its border -> forecast in Bangladesh only with 2 or 3 days lead time.
- Study purpose: Use satellite-based water elevation upstream in India to forecast water elevation at the gauge locations (India/ Bangladesh border).

Data used: in-situ measurements

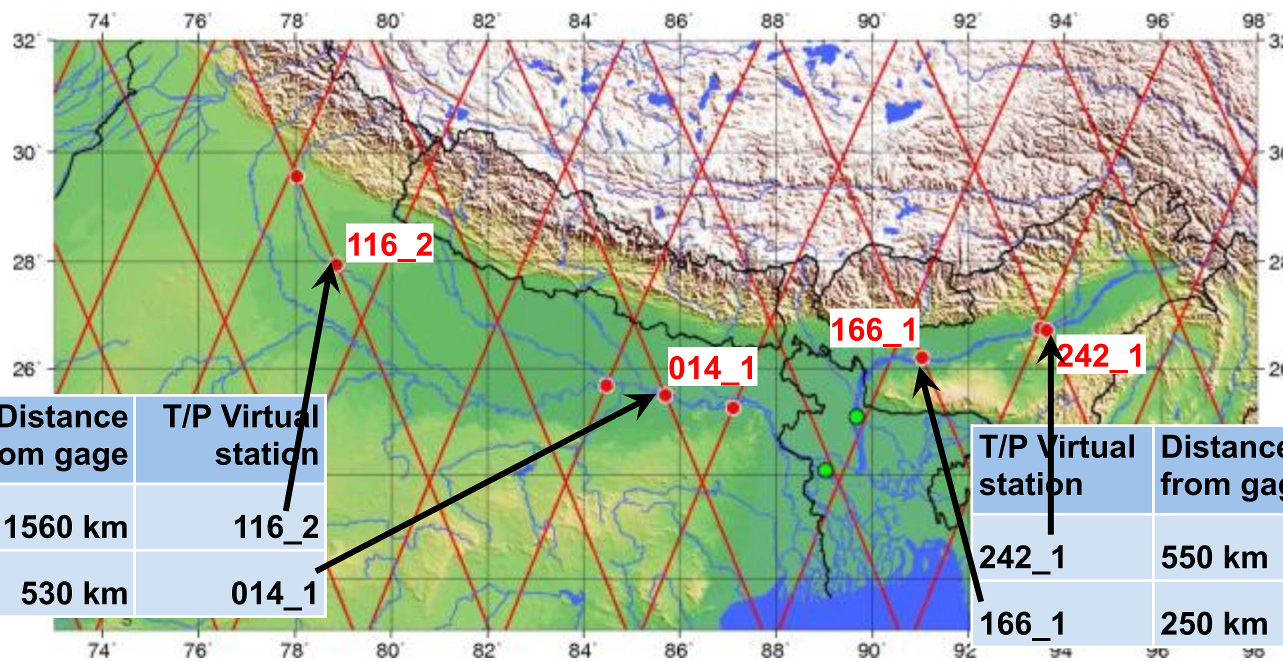


Brahmaputra: gauge at Bahadurabad (Average river width~10km)

Ganges: gauge at Hardinge Bridge (Average river width~5km)

Data used: satellite altimetry

- Topex/Poseidon (T/P) satellite altimeter.
- Overlap with in-situ: January 2000/August 2002.
- Data downloaded from HYDROWEB: http://www.legos.obs-mip.fr/en/soa/hydrologie/hydroweb/



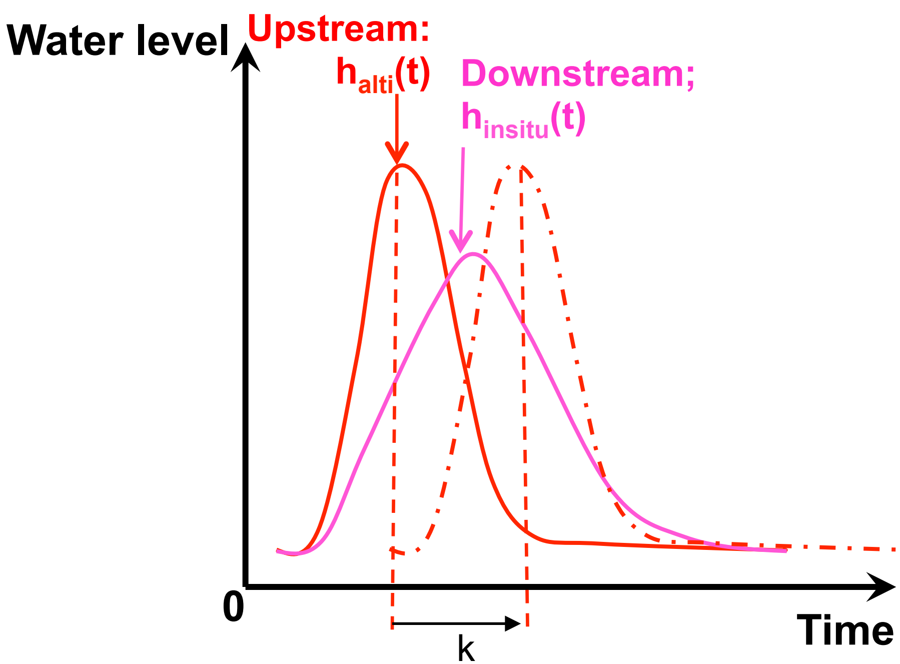
Mean time between obs.	Distance from gage	T/P Virtual station
12 days	1560 km	116_2
22 days	530 km	014_1

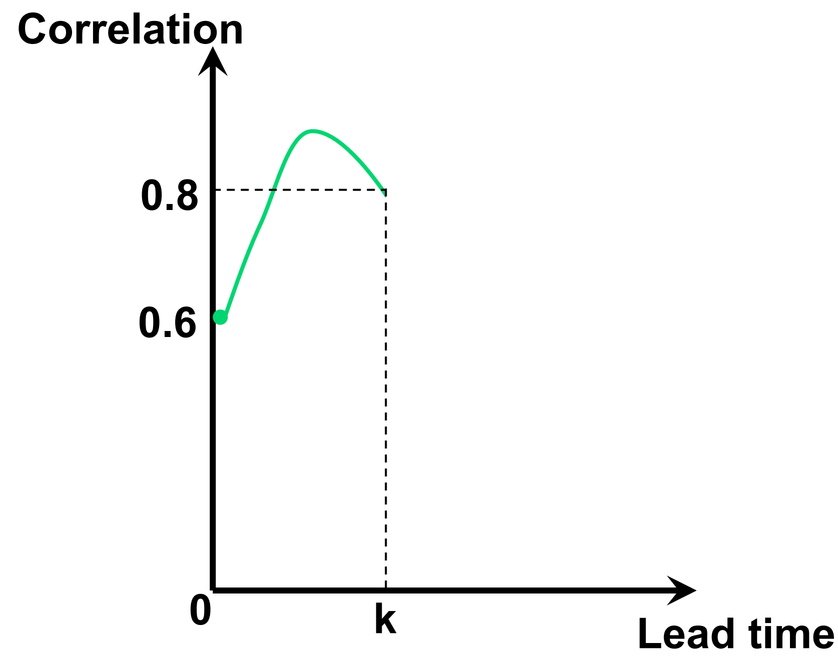
T/P Virtual station	Distance from gage	Mean time between obs.
242_1	550 km	14 days
166_1	250 km	16 days

Methodology 1/2

- Compute the cross-correlation between upstream T/P and in-situ measurements:

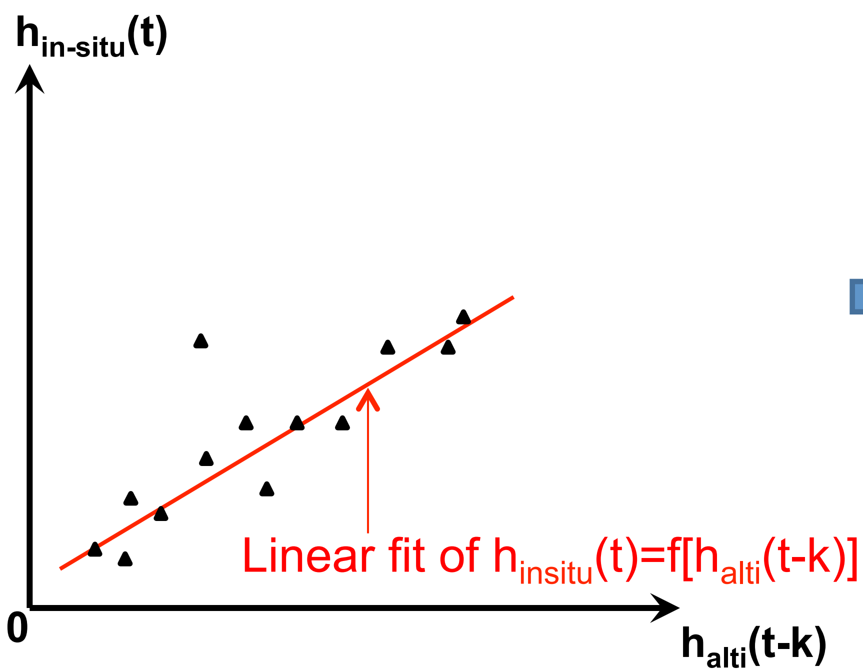
$$Correlation(k) = \frac{\mathrm{cov}\left[h_{insitu}(t), h_{alti}(t-k)\right]}{\mathrm{stdev}\left[h_{insitu}(t)\right] \cdot \mathrm{stdev}\left[h_{alti}(t-k)\right]}$$ with k=lead time

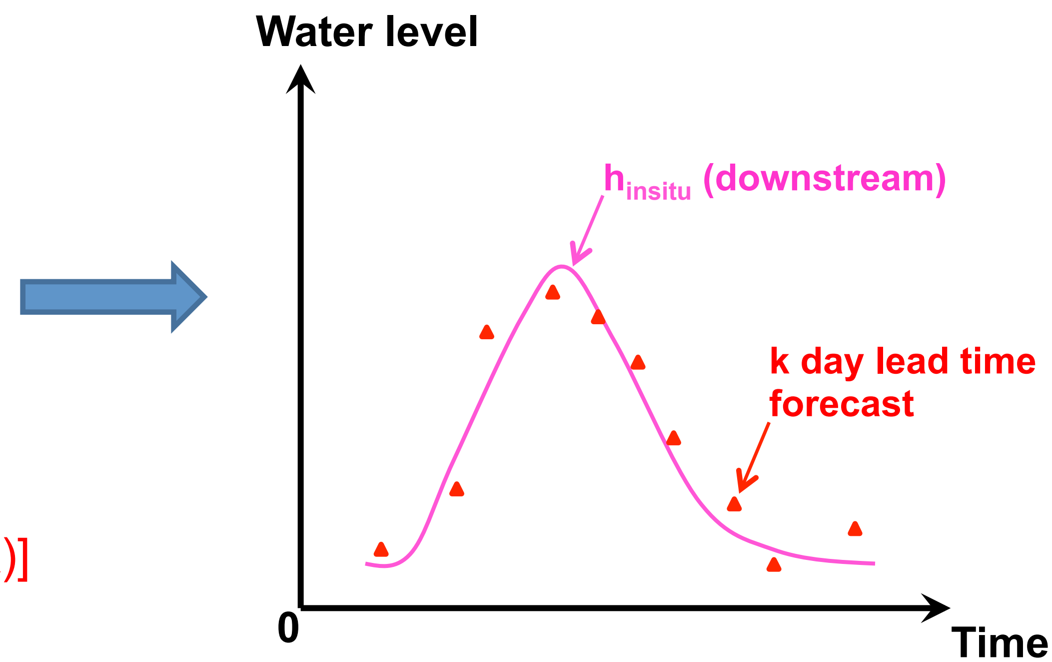




Methodology 2/2

- Compute scatter plot in-situ measurements & T/P measurements k days earlier.
- Use linear fit to forecast water level at gauge location from T/P measurements.

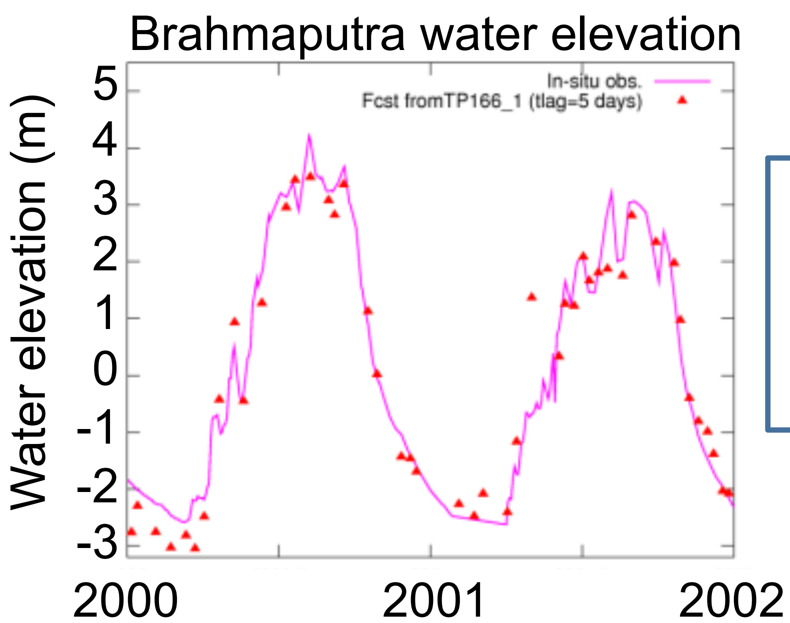




Results on the Brahmaputra

- 5-day lead time Forecasts:

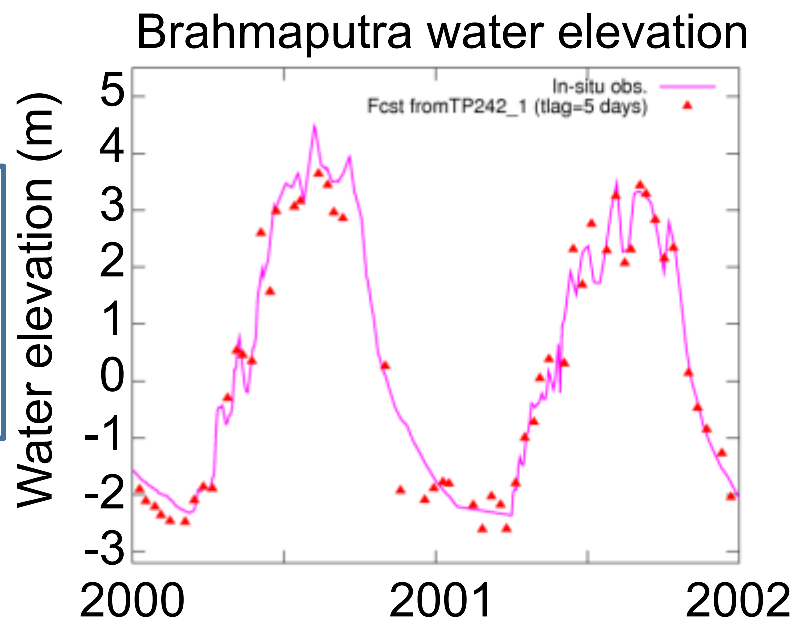
T/P virtual station 250 km upstream:



5-day forecast
RMSE ~ 0.5 m

Legend:
In-situ
T/P forecast

T/P virtual station 550 km upstream:

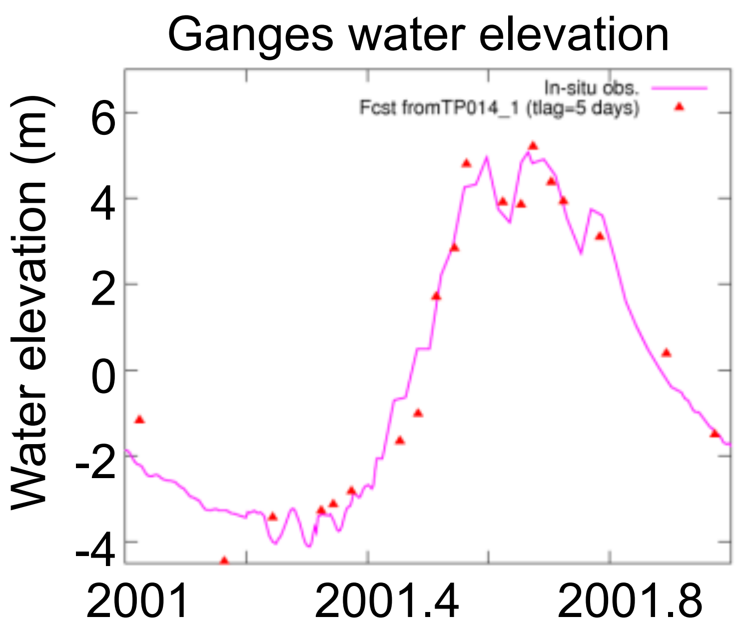


5-day forecast
RMSE ~ 0.5 m

Results on the Ganges

- 5-day lead time forecast:

T/P virtual station 530 km upstream:

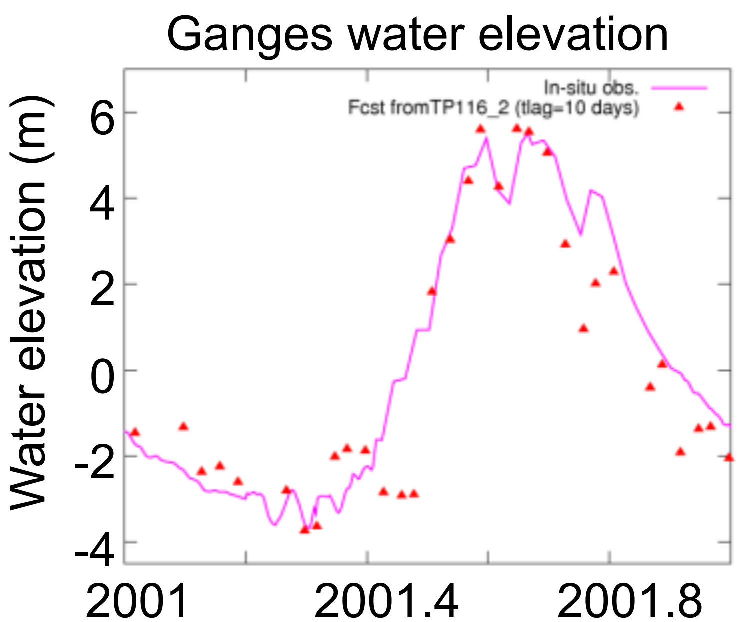


5-day forecast
RMSE ~ 0.6 m

Legend:
- In-situ
- T/P forecast

- 10-day lead time forecast:

T/P virtual station 1560 km upstream:



10-day forecast
RMSE ~ 0.9 m

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Department of Civil and Environmental Engineering

Global Monitoring of Large Reservoir Storage from Satellite Remote Sensing




Huilin Gao[1], Dennis P. Lettenmaier[1], Charon Birkett[2]

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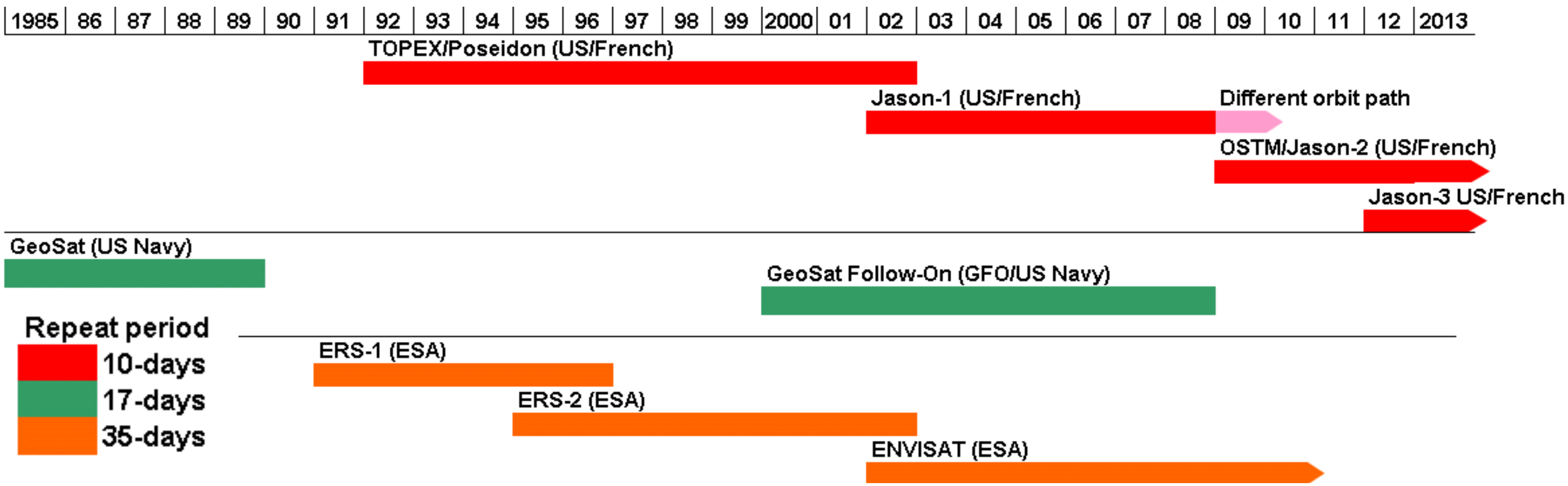
Background and Challenges

Water surface level

General Timeline for Satellite Radar Altimeters



USDA Global Reservoir and Lake Elevation Database
French Space Agency's Hydrology by Altimetry (LEGOS)
European Space Agency (ESA) River & Lake

Limitations of altimetry products

- Only retrieve heights along a narrow swath determined by the footprint size
- Satellite path must be at least 5km over the body of water
- Complex topography causes data loss or non-interpretation of data

Future opportunity: The Surface Water Ocean Topography mission (SWOT)

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Background and Challenges

Water surface area

× No dynamic water classification product available

?? ***Most currently available multi-reservoir surface area estimations are from a hybrid of sensors (Landsat, MODIS, ASAR)***

- ***lack of consistency*** ***lack of validation***

Objective

A validated reservoir water area dataset which is based on observations from the same instrument and classified using the same algorithm is essential

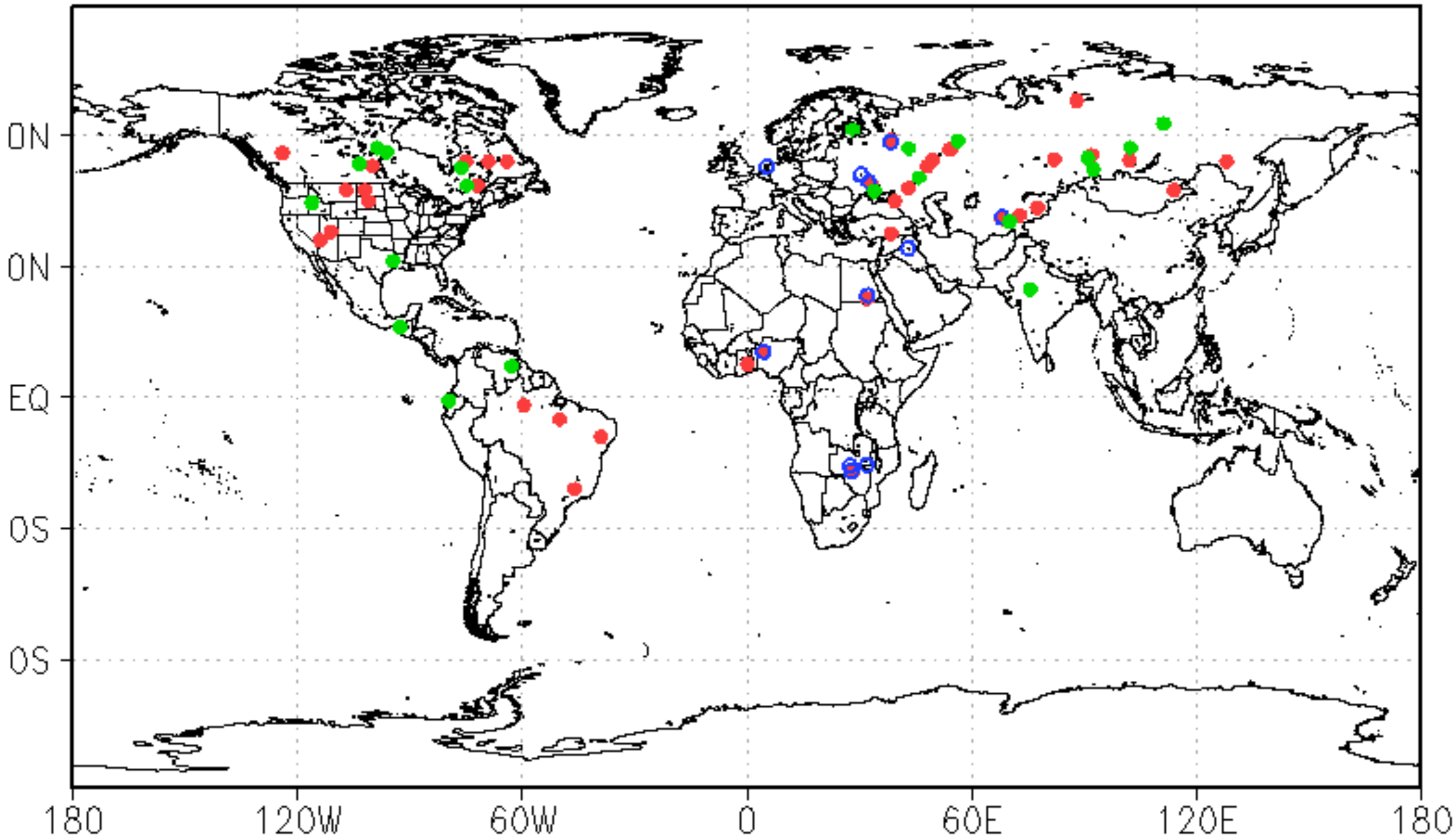
Unsupervised classification

MODIS 16-day global 250m vegetation index

MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard the Terra (2000~) and Aqua (2002~) satellites

Reservoir Surface Levels from Altimetry

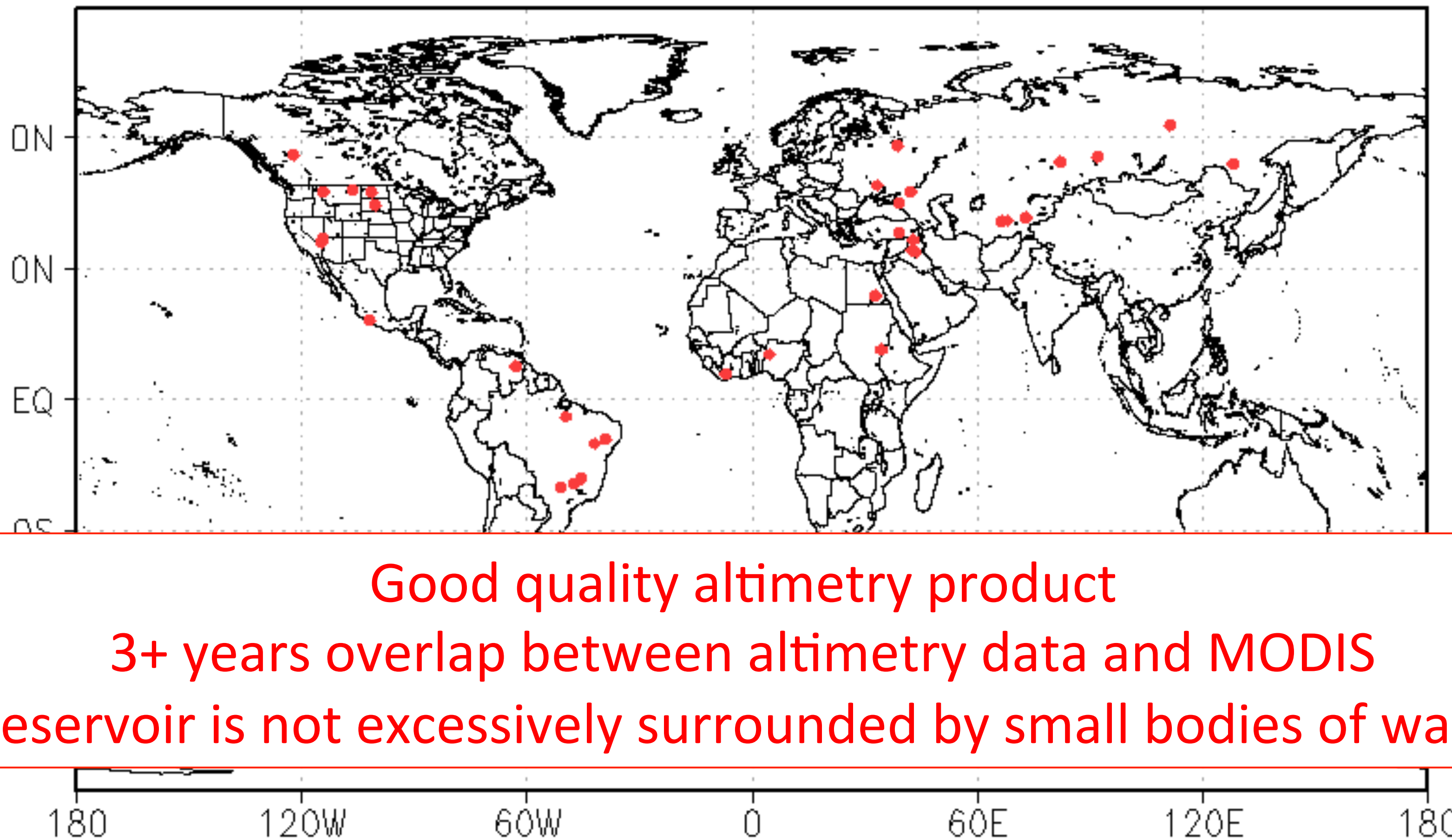
LEGOS: 36   USDA: 15   UW (T/P):20   **Total: 62**



T/P: Topex/Poseidon (1992-2002)

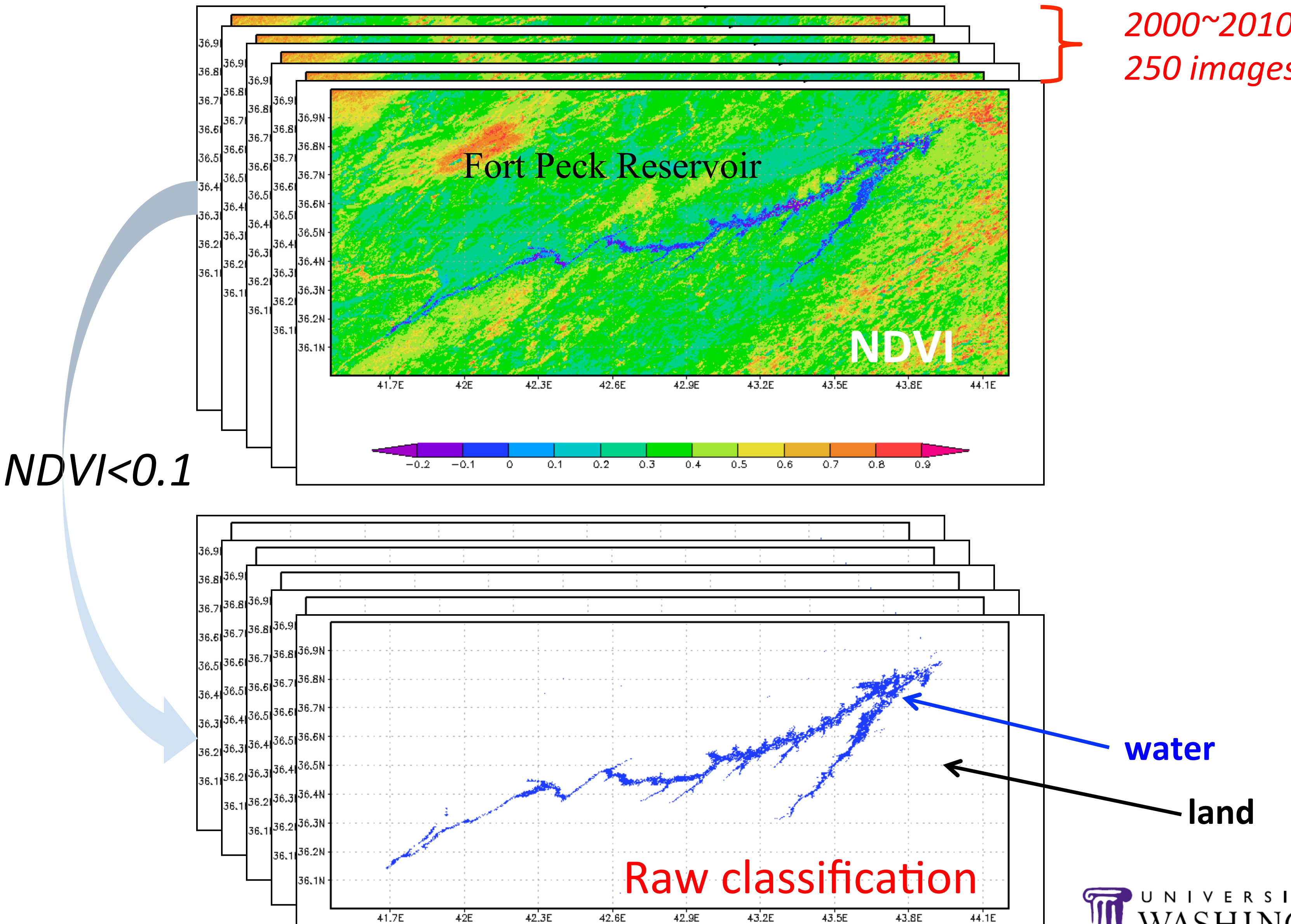
Reservoir Selection

A total of 34 reservoirs (1164 km^3, 15% of global capacity)



Good quality altimetry product
3+ years overlap between altimetry data and MODIS
Reservoir is not excessively surrounded by small bodies of water

Method: Water Classification



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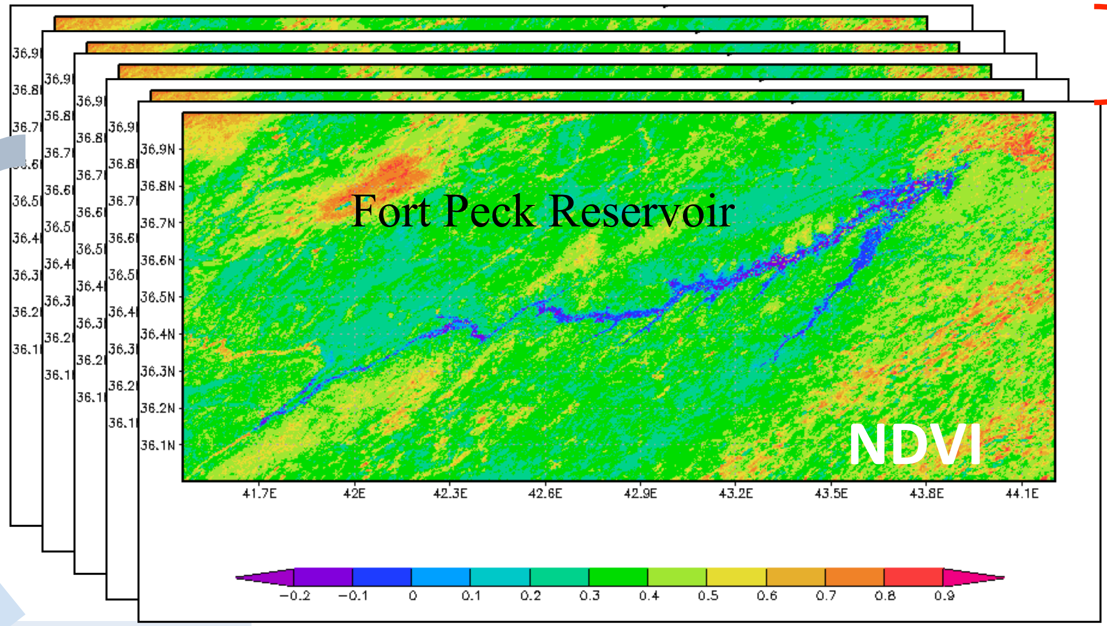
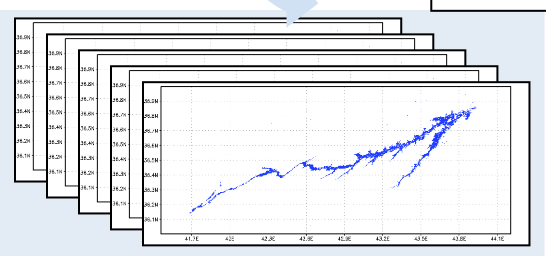
Method: Water Classification

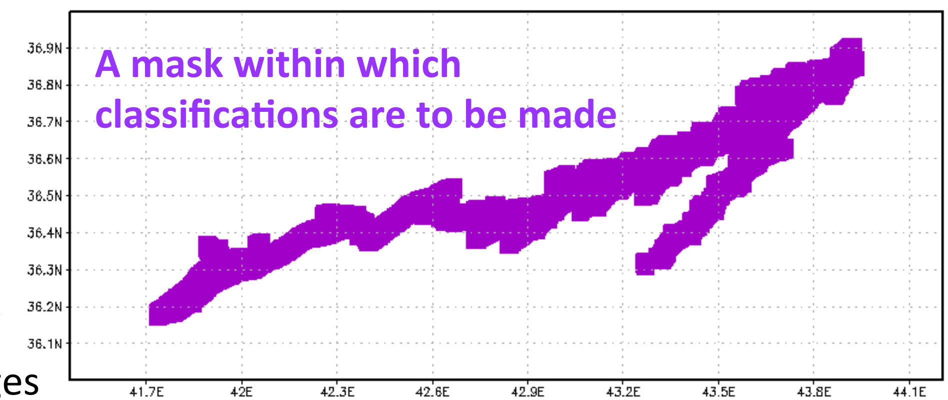
2000~2010
250 images



NDVI<0.1



Pixel frequency of the 250 images



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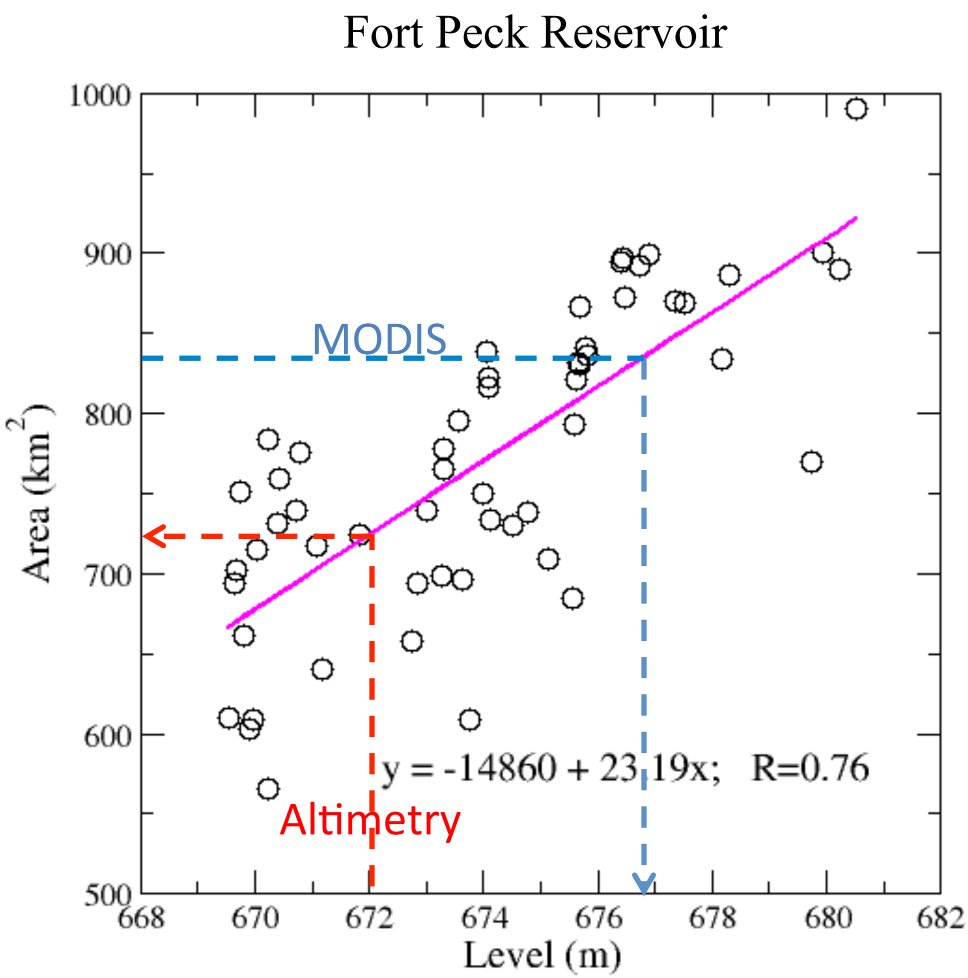
Method: Level-Area Relationship



Storage Estimation

$h_o \rightarrow A_o$

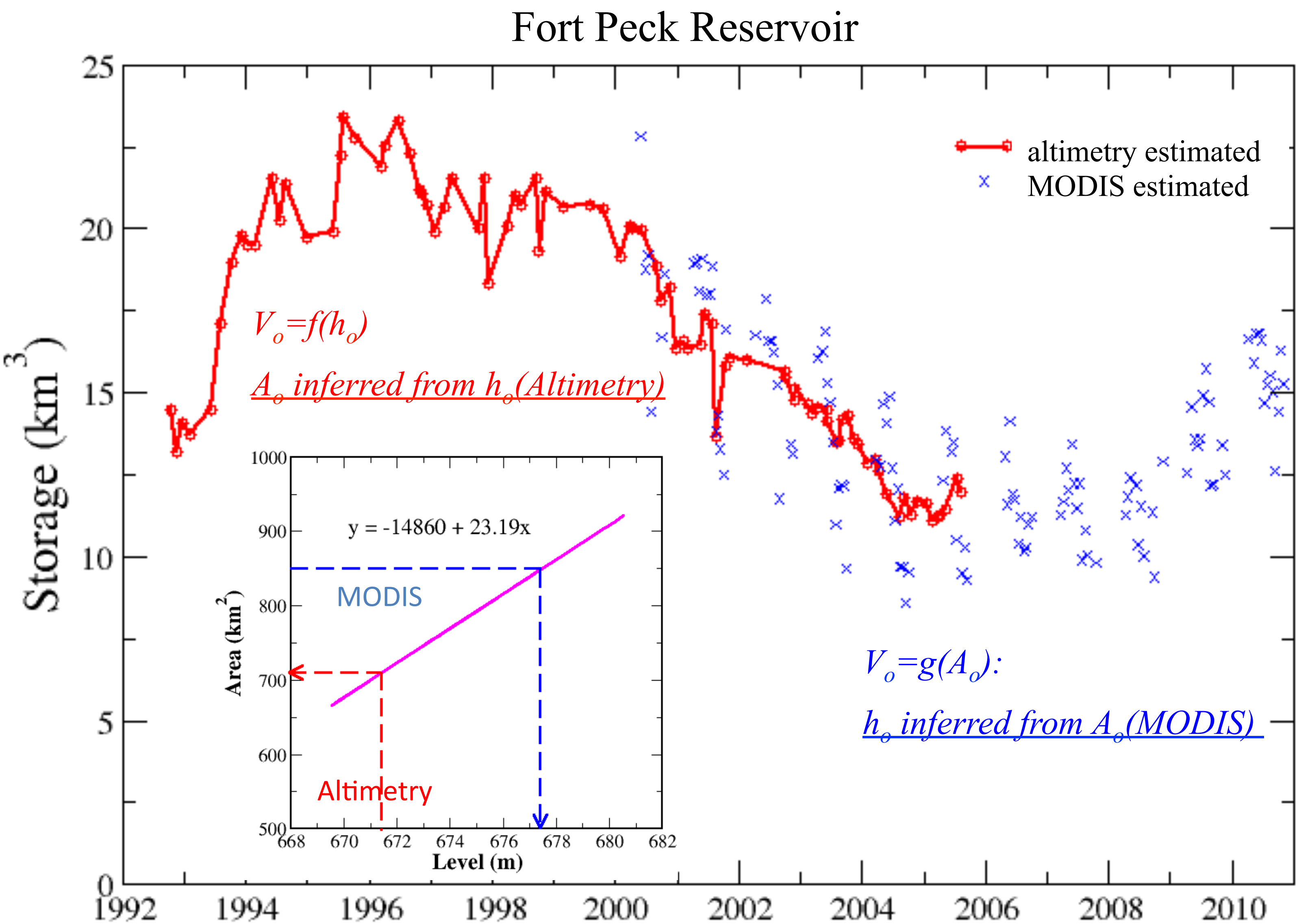
$A_o \rightarrow h_o$

$$V_o = V_c - (A_c + A_o)(h_c - h_o)/2$$

$$V_o = f(h_o) \text{ or } V_o = g(A_o)$$

Variables at capacity from Global Reservoir and Dam database (Lehner et al., 2011)

Method: Storage Estimation



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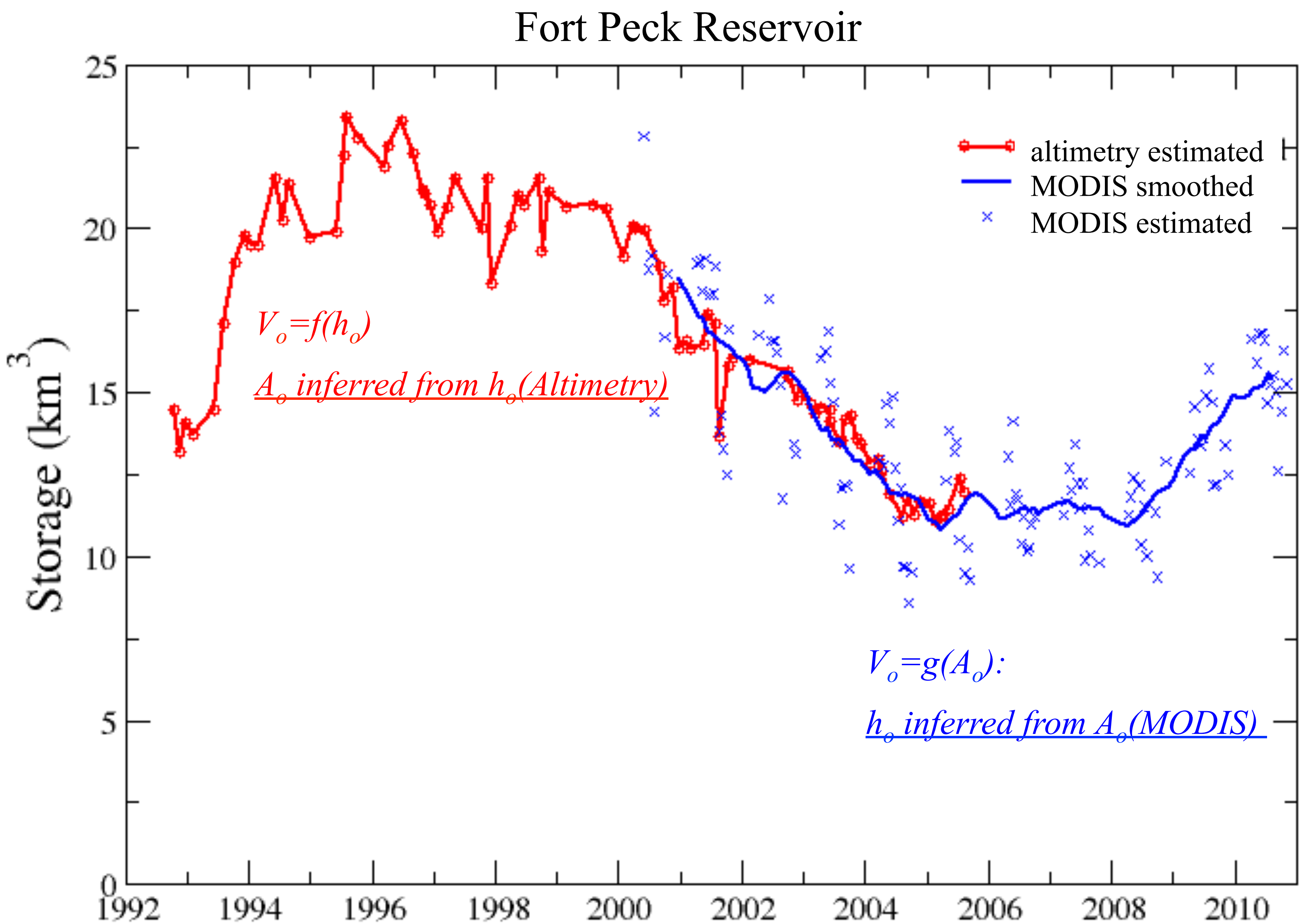
Method: Storage Estimation



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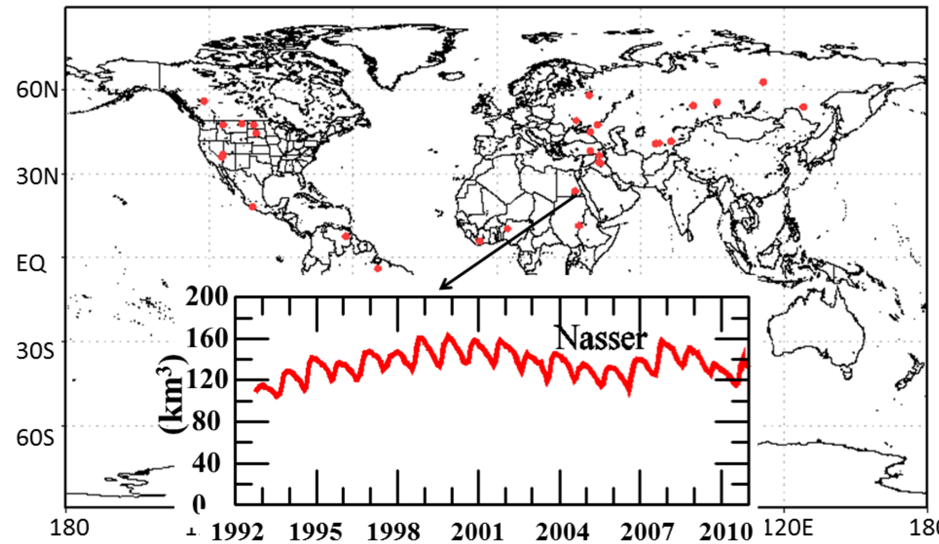
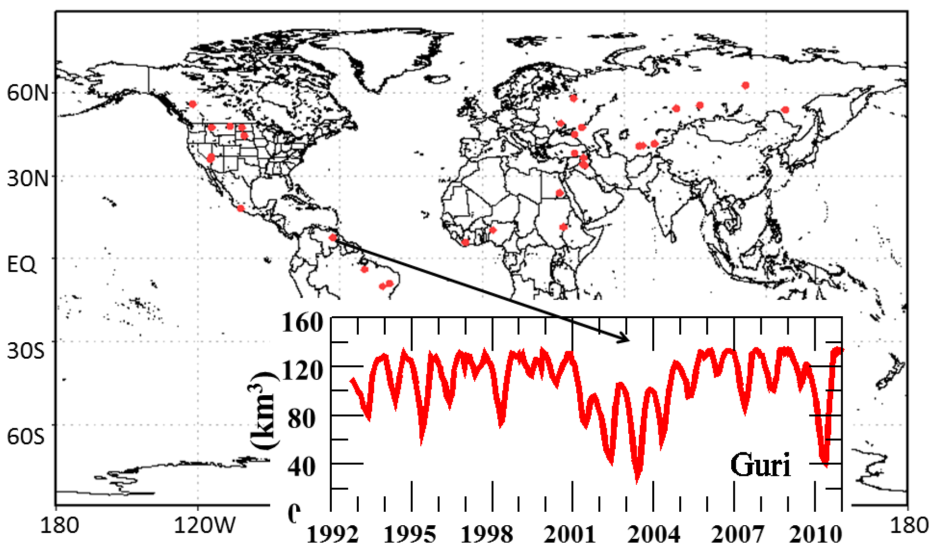
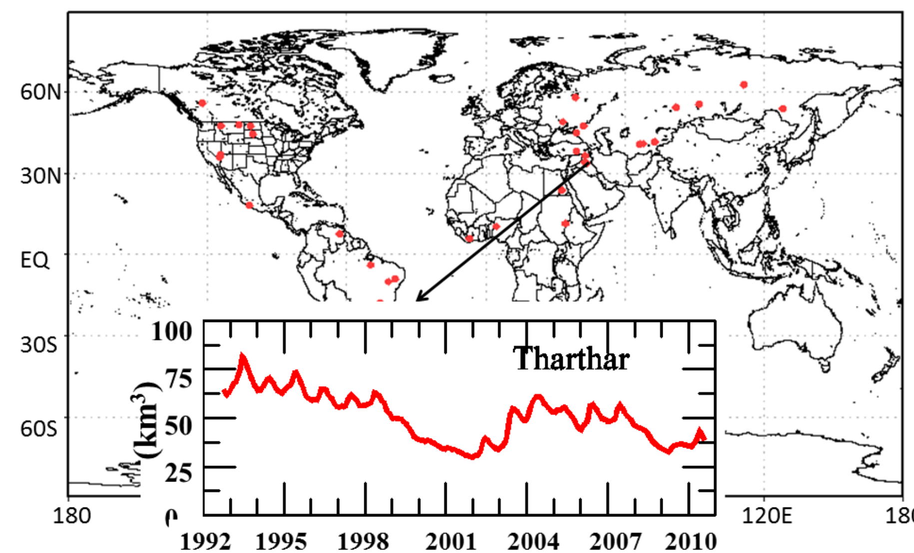
Global reservoir storage product, 1992-2010







Conclusions

- ✓ An unsupervised classification method was applied to the MODIS vegetation index data to estimate reservoir surface area from 2000 to 2010

- ✓ Level-area relationships were derived for each of the 34 reservoirs, such that the remotely sensed depth and area can be used jointly to maximize observation length

- ✓ The estimated reservoir storage, surface area, and water level were validated by gauge data over the five largest US reservoirs

- ✓ A 19-year consistent global reservoir dataset (including storage, surface area, and water level) was derived

- ✓ The remotely sensed reservoir storage estimations can be used for operational applications and hydrologic modeling of water management

Summary

Three examples (two involve applications of macroscale hydrology modeling to large scale hydrologic prediction):

1) **Northern Eurasian CH_4: Modeling lakes and saturated extent is the key**
2) **Seasonal hydrologic prediction: Skill is mostly in hydrologic ICs; modest skill improvements may be possible relative to classic ESP approaches**
3) **More can be done to exploit current (and past) altimeters for hydrologic prediction and water cycle applications, but SWOT will greatly expand the frontier**